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TECHNICAL ADVANCE

Nature 4.0: A networked sensor system for integrated biodiversity monitoring

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Abstract

Ecosystem functions and services are severely threatened by unprecedented global loss in biodiversity. To counteract these trends, it is essential to develop systems to monitor changes in biodiversity for planning, evaluating, and implementing

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conservation and mitigation actions. However, the implementation of monitoring systems suffers from a trade-off between grain (i.e., the level of detail), extent (i.e., the number of study sites), and temporal repetition. Here, we present an applied and realized networked sensor system for integrated biodiversity monitoring in the Nature 4.0 project as a solution to these challenges, which considers plants and animals not only as targets of investigation, but also as parts of the modular sensor network by carrying sensors. Our networked sensor system consists of three main closely interlinked components with a modular structure: sensors, data transmission, and data storage, which are integrated into pipelines for automated biodiversity monitoring. We present our own real-world examples of applications, share our experiences in operating them, and provide our collected open data. Our flexible, low-cost, and open-source solutions can be applied for monitoring individual and multiple terrestrial plants and animals as well as their interactions. Ultimately, our system can also be applied to area-wide ecosystem mapping tasks, thereby providing an exemplary cost-efficient and powerful solution for biodiversity monitoring. Building upon our experiences in the Nature 4.0 project, we identified ten key challenges that need to be addressed to better understand and counteract the ongoing loss of biodiversity using networked sensor systems. To tackle these challenges, interdisciplinary collaboration, additional research, and practical solutions are necessary to enhance the capability and applicability of networked sensor systems for researchers and practitioners, ultimately further helping to ensure the sustainable management of ecosystems and the provision of ecosystem services.

KEYWORDS
animal tracking, audio recording, camera trap, integrated database system, nature conservation, radar, remote sensing, telemetry

1 | INTRODUCTION

Global change and the resulting unprecedented global biodiversity loss are major threats to human wellbeing (Steffen et al., 2015). With the present warming of about 1°C relative to the preindustrial average (Hoegh-Guldberg et al., 2019), we are already experiencing extreme weather events such as the increasing frequency of heat waves, droughts, and flooding (Allan et al., 2018). Consequently, comprehensive efforts are required to protect biodiversity and its associated critical ecosystem functions and services, which are threatened by global change (Leclère et al., 2020). For planning and implementing biodiversity conservation and mitigation actions as well as for evaluating their success, biodiversity monitoring approaches fall under three different categories (Eyre et al., 2011; Sparrow et al., 2020): (1) *Targeted monitoring* based on detailed field observations across a limited number of study sites in order to close research gaps related to individual or population-specific cause-and-effect relationships; (2) *Surveillance monitoring* based on more general field studies across many sites, over larger areas, and including multi-annual repetitions in order to observe changes of populations or communities; and (3) *Landscape monitoring* for a wall-to-wall mapping of environmental changes on a community to ecosystem level.

All monitoring approaches face a trade-off between grain (i.e., the level of detail), extent (i.e., the number of study sites), and temporal repetition. A solution to this challenge is often sought in remote sensing data. For example, Pettorelli et al. (2016) proposed a set of Satellite Remote Sensing Essential Biodiversity Variables (SRS-EBVs) for substituting field observations. Stating that biodiversity measures, such as ecosystem structure, fractional vegetation cover, leaf area index, or vegetation phenology can be derived using data from global space programs like NASA's Earth Observing System, the EU's Copernicus program, or the recently launched German EnMAP satellite. However, SRS-EBVs all depend on the spectral properties of larger vegetation or landscape features. Consequently, more specific biodiversity measures such as species' populations, species' traits, or the community composition of plants and animals are more difficult to monitor as they are not directly related to radiative transfer.

In order to monitor and map indirect biodiversity measures, machine learning modelling approaches are potential solutions, but they depend on ground truth data for training and testing. Unfortunately, the targeted and surveillance monitoring approaches cannot provide these data due to the aforementioned trade-off between grain, extent, and temporal repetition of the observations, hence these are not suitable for closing the systematic biodiversity monitoring gap. Thus, more integrated monitoring systems are needed.

Networked sensor systems have the potential to close the systematic monitoring gap between field observations of biodiversity measures and wall-to-wall remote sensing mappings. They allow practitioners to realize a dense observation network with biodiversity status information in near real-time, which would not be possible with field observations alone. In addition, networked sensor systems provide the data needed for training and testing machine learning models in conjunction with remote sensing data.

There have been considerable efforts in recent years to establish and operate networked sensor systems for biodiversity monitoring from the first vision of "sensing biodiversity" (Turner, 2014) towards the idea of fully automated global biodiversity monitoring (Besson et al., 2022; Bohan et al., 2017; Steenweg et al., 2017). For example, Sethi et al. (2018) introduced an open-source low-cost modular device for long-term continuous camera and audio recordings, and Wägele et al. (2022) presented a prototype of automated multisensor stations for monitoring species diversity (for reviews of biodiversity monitoring technologies, see Allan et al., 2018; Besson et al., 2022; Lahoz-Monfort & Magrath, 2021). However, there is still a pressing need to combine and integrate various biodiversity monitoring technologies for the automated monitoring of multi-species systems *under real-world conditions*, to proceed from an initial vision to a practical realization, which can have a significant impact on the conservation of biodiversity, and ultimately secure ecosystem functions and services.

2 | THE NATURE 4.0 PROJECT

Here, we present the achievements of practically realizing a networked sensor system for integrated biodiversity monitoring in the Nature 4.0 project. The research and teaching forest of the University of Marburg in Germany—the Marburg Open Forest—served as the primary testbed for the development of our networked sensor system.

In the Nature 4.0 project, we propose a change in perspective that does not consider plants and animals to be mere variables for monitoring, but which utilizes them as parts of a modular monitoring infrastructure. The Nature 4.0 networked sensor system comprises three main technical components with a modular structure: sensors, data transmission, and data storage (Figure 1). We present exemplary applications for biodiversity monitoring using data obtained in the Nature 4.0 project with static and mobile sensors.

2.1 | Sensors and their applications

All sensors of the Nature 4.0 network are modular and can be omitted, expanded, or adapted as needed. The static and mobile sensors facilitate monitoring without permanent supervision by researchers and practitioners, are intentionally inexpensive, and largely open-source. As open science is a core theme in the Nature 4.0 project, all of the collected data and computer code is available in online databases or from the authors upon request.

2.1.1 | Tracking

tRackIT: An open-source radio tracking system for bats and small animals

Bats represent an ecologically significant taxonomic group as they are globally significant to maintain healthy ecosystem functioning through pollination and dispersal of seeds (Kunz et al., 2011). Despite their important contributions to human wellbeing, knowledge of their behaviour is limited, especially in comparison to larger-bodied mammals and birds (Frick et al., 2020). Direct observation of bats is hampered by their particularly small body size, fast and abrupt movements, and nocturnal lifestyle. In traditional conservation monitoring approaches, bats are often studied using manual radio tracking (Naďo et al., 2019), which can be inefficient due to time requirements and the high cost of the specialized labour required.

To reduce the amount of manual labour required to track bats, we developed an open-source system for reliable automatic radio tracking of (small) animals in situ (*tRackIT* Systems; https://trackit.systems; Gottwald et al., 2019; Höchst et al., 2021). *tRackIT* acquires, stores, analyses, and transmits captured very high frequency (VHF) signals and their descriptive features, to carry out activities such as calculation of the bearing of signals emitted by VHF radio tags attached to animals or the classification of animal activity (Gottwald et al., 2022). Tracking data were stored in an influx database (InfluxDB, https://www.influxdata.com), with associated metadata being stored in a MySQL database (https://www.mysql.com).

Furthermore, to overcome the limitations of traditional monitoring methods, such as low capture rates of small animals on camera traps, we developed a more flexible multi-sensor solution consisting of off-the-shelf consumer electronics (*BatRack*; Gottwald et al., 2021; https://nature40.github.io/BatRack/; Figure 2). *BatRack* is a multi-sensor solution that combines the individual methods for monitoring of bats, consisting of automatic VHF radio tracking, as well as audio and video recording combined in a single platform. Each sensor can be used as a trigger for the other. Using these methods in combination led to >90% detection rates in camera recordings when the echolocation calls of bats were used as a trigger. The use of multiple sensors also facilitates the detection of individuals in videos, since VHF signal patterns can be matched with the video recordings. Thus, *BatRack* facilitates detailed observations of the behaviour of individual bats over long durations. Visual behavioural observations can be linked to vocalization and to VHF signal patterns, which enables the training of machine learning classifiers that automatically detect behavioural states in sound recordings and tracking

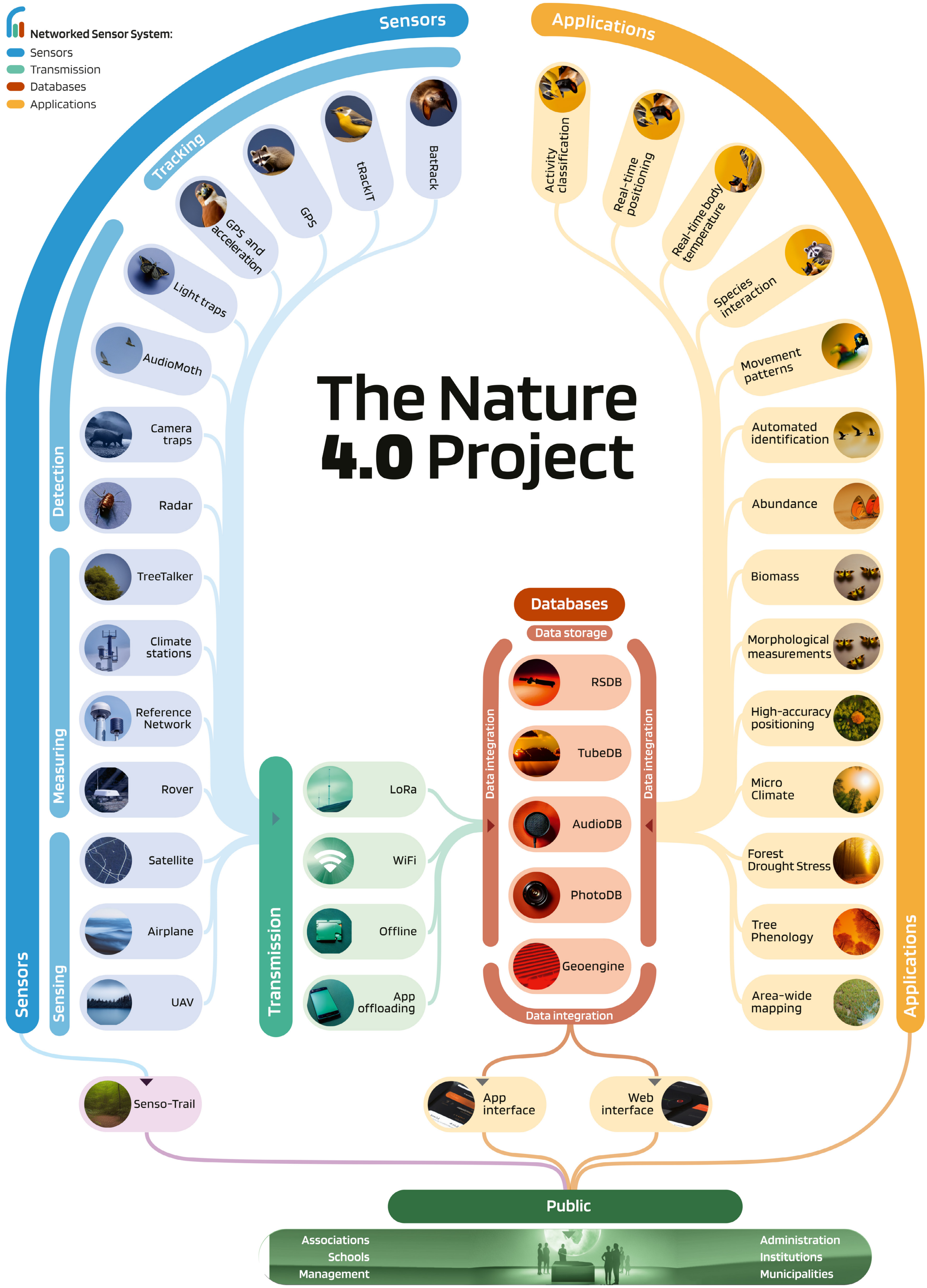
Networked Sensor System:
Sensors
Transmission
Databases
Applications
Sensors
Tracking
BatRack
tRackIT
GPS
GPS and acceleration
Light traps
AudioMoth
Detection
Camera traps
Radar
Measuring
TreeTalker
Climate stations
Reference Network
Rover
Sensing
Satellite
Airplane
UAV
Transmission
LoRa
WiFi
Offline
App offloading
The Nature 4.0 Project
Databases
Data storage
Data integration
RSDB
TubeDB
AudioDB
PhotoDB
Geoengine
Applications
Activity classification
Real-time positioning
Real-time body temperature
Species interaction
Movement patterns
Automated identification
Abundance
Biomass
Morphological measurements
High-accuracy positioning
Micro Climate
Forest Drought Stress
Tree Phenology
Area-wide mapping
Senso-Trail
App interface
Web interface
Public
Associations
Schools
Management
Administration
Institutions
Municipalities

FIGURE 1 The Nature 4.0 project. The core of the Nature 4.0 project is the networked sensor system, which comprises three main components: sensors, data transmission, and data storage. These components of the sensor network are modular and adjustable depending on the biodiversity element in focus. Readily accessible open-source databases were developed specifically to address each application's data storage requirements, and facilitate data transfer to other elements of the network and wider public. The public is also integrated via the SENSO-Trail (Science Education and Natural System Observation), with guided tours, school fieldtrips, and online open educational resources. The modular design of the Nature 4.0 project allows for both targeted and surveillance monitoring of biodiversity, and can, in combination with data upscaling methods, be used for seamless area-wide biodiversity mapping in near real-time, with a range of potential applications.

FIGURE 2 *BatRack*. *BatRack* is a multi-sensor monitoring solution that combines individual methods for the monitoring of bats, consisting of automatic VHF radio tracking, as well as audio and video recording combined in a single platform (a). Each sensor can be used as a trigger for the other, thereby strongly improving detection rates. *BatRack* allows researchers to efficiently collect data on species occurrences at a very high spatiotemporal resolution and can reliably operate in various environments (a–c). Photos: P. Lampe (a), J. Gottwald (b), V. Salewski (c).

data. Linking the use of space to the behaviour of individuals helps to better assess the ecological function of habitats and facilitates targeted conservation measures.

Animal behaviour at local scales

Knowledge about the activity periods of animals throughout the day provides important ecological insights into their responses and adaptations to the environment, foraging strategies, energetics, and interactions with other individuals or species (Torney et al., 2021). However, there are no available methods that track both the activity and habitat use of small taxa in the wild, particularly in areas of dense vegetation such as forests. Within the Nature 4.0 project, we were able to partially overcome this limitation.

Subject tracking in forested environments remains challenging. However, we can now measure activity at high temporal resolution by using our automated radio tracking system (*BatRack* and *tRackIT*) in combination with a machine learning approach that allows us to distinguish when individuals are active or at rest (Gottwald et al., 2022). Our approach offers various novel opportunities to investigate species interactions in forest ecosystems by providing fine-scale insights into the activity patterns of animals such as bats and songbirds. For instance, we are now able to assess the extent to which forest-dwelling bats and forest birds overlap in the timing and intensity of their daily activity (Gottwald et al., 2022), and to explore group decision making mechanisms in the wild such as bat roost switching and associated swarming behaviour.

The activity classification in the Nature 4.0 project was possible with high accuracy and at high temporal resolution, although the spatial resolution and coverage of the VHF tracking data is dependent on the positioning of the station network and is influenced by the surrounding landscape. With a median localization error of approximately 40 m in forested and hilly terrain, the spatial resolution is suitable for many future research questions.

In 2022, VHF tracking of birds and bats was complemented by conventional GPS tracking of racoons, an invasive predator species (Figure 3). Combined with fine-scale habitat and weather monitoring, this multi-species tracking has the potential to provide new insights into the spatiotemporal interactions of species with their environment.

Birds at larger scales

Birds are highly mobile and many species, particularly migratory ones, inhabit larger areas throughout the year (Newton, 2008). As a consequence, local tracking solutions like *tRackIT* will often be insufficient to cover their movement over larger scales. Today, biologging technologies facilitate the investigation of animal movements with few of the limitations imposed by the spatial scale, long-distance migration, animal's visibility, roughness of the terrain, or remoteness of the locations (Brown et al., 2013; Jetz et al., 2022). After the animal

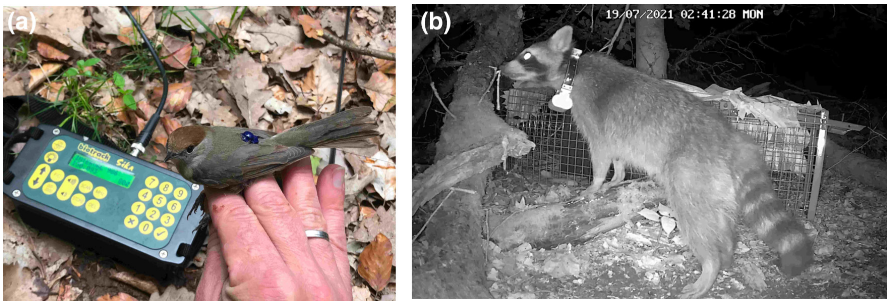

FIGURE 3 Handling of a tagged female Eurasian blackcap (a, *Sylvia atricapilla*). The tiny (<0.6 g) VHF tag is mounted on the back of the bird using a figure-eight harness, with a handheld Yagi antenna for mobile activity and location tracking. Photo: S. Rösner. A female racoon (*Procyon lotor*) equipped with a GPS-GSM collar visiting a baited walk-in trap (b). Photo: S. Rösner via remote camera control.

has been tagged, biologging technologies also allow the investigation of animal behaviour without the disturbance introduced by the presence of an observer (Shepard et al., 2008).

Commercially available solar-powered GPS and tri-axial acceleration trackers (such as Ornitrack transmitters, Ornitela, Lithuania; trackers weigh 9 g and up; suitable for birds >270 g) allow the collection and transmission via GSM of large quantities of fine-scale information recorded at high frequency, thereby capturing rapid changes in acceleration whilst the animal motion. The trackers generated a sizable quantity of data and metadata (1,225,228 GPS locations, >130,000,000 tri-axial acceleration data points by 28 September 2023), which were archived in the Movebank repository (IDs 746410443, 897868497; https://www.movebank.org). This information allows researchers to investigate a range of ecological questions on topics like habitat selection, behavioural adaptations to the environment, energy and activity budgets, energy use and predator avoidance (Masello et al., 2017, 2021), and movement patterns via machine learning classification of the behaviour of the birds. In 2023, using machine learning algorithms (Random Forest, Support Vector Machine and Extreme Gradient Boosting), we were able to categorize the behaviour of Common Woodpigeons (*Columba palumbus*) into three main patterns, which are foraging, flying, and resting and calculated time budgets over the breeding and winter season (Figure 4a,b; Masello et al., 2023).

In 2020, space-based tracking technology, like the International Cooperation for Animal Research Using Space (ICARUS) receiver aboard the Russian module of the International Space Station enabled the use of low-cost miniature tags to investigate animal movement (Jetz et al., 2022). This technology facilitated the fine-scale tracking of medium-sized species like the Eurasian Jay (*Garrulus glandarius*) in the Marburg Open Forest. During 2021, nine Eurasian Jays were fitted with 5 g ICARUS tags (Figure 4c), which precisely recorded their positions, enabling the investigation of the use of the forest and adjacent habitats by this species (Figure 4d). Unfortunately, the Russian space agency ceased its cooperation with ICARUS on the ISS, thus data transmissions from the International Space Station were terminated in March 2022 (https://www.icarus.mpg.de/en). Currently, ICARUS is exploring options to establish alternative data transmission approaches (Wikelski et al., 2007).

2.1.2 | Detection

Bird species in soundscapes

Birds are the target of several biodiversity monitoring programs because they are vocal and thus relatively easy to monitor (Bibby et al., 2000), their response to anthropogenic change is often correlated to other taxa (Gregory et al., 2005), and they contribute to ecosystem services in a variety of ways (Sekercioglu, 2006). Despite their relevance, we not only continue to lose bird species (IPBES, 2019) but also a sharp decline in breeding bird abundance in North America and Europe has been observed in recent decades (Inger et al., 2015; Rosenberg et al., 2019). To adequately assess the current state of bird communities and counteract the ongoing loss of biodiversity, autonomous sound recorders ("AudioMoth", Hill et al., 2018) were deployed in the Nature 4.0 project as cost-effective devices for high-resolution monitoring (Wägele et al., 2022).

Rapidly evolving deep learning methods, such as convolutional neural networks (CNN), effectively support the automated identification of different species from AudioMoth recordings (Kahl et al., 2021; LeBien et al., 2020; Ruff et al., 2020). However, autonomous sound recordings so far show considerable differences in the composition of identified bird communities compared to field surveys (Blake, 2021; Pérez-Granados et al., 2019). To improve the congruency between autonomous sound recordings and manual bird surveys, we trained machine learning models to simultaneously detect and identify different bird species in audio recordings. For this purpose, novel neural network architectures, pre-processing schemes, and training strategies were developed and investigated. Our approach is based on a neural architecture search (Mühling et al., 2020) and was the winner of the international BirdCLEF 2020 challenge (https://www.imageclef.org/BirdCLEF2020). Overall, our findings show that the automated monitoring revealed not only similar results for species diversity, but also for the bird community composition compared to the expert surveys, which are particularly relevant for conservation.

To overcome the disadvantage of the data collection phase of otherwise autonomous sound recording, we have developed Bird@Edge, an edge artificial intelligence (AI) system for recognizing bird species in audio recordings to support near real-time biodiversity

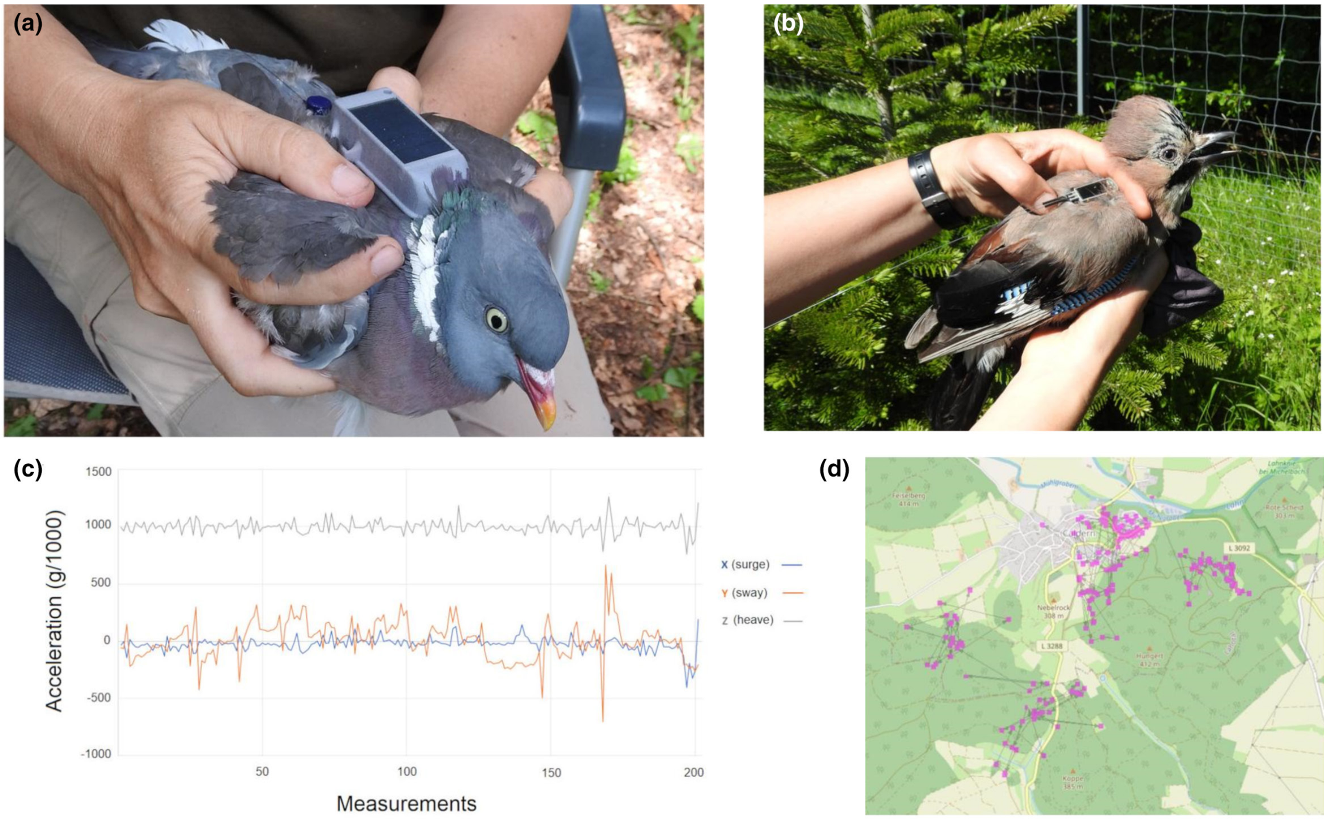

FIGURE 4 Use of biologging technologies to infer behaviour and habitat use. Common Woodpigeon (*Columba palumbus*) with OrniTrack-15 solar-powered GPS-GSM/GPRS trackers during deployment (a, Photo: S. Rösner), and representative burst corresponding to dynamic acceleration during feeding behaviour of this species (c). We represented acceleration (in g/1000, as received from the sensor), using colored continuous lines: blue in for the surge *x*-axis, orange for sway (*y*-axis), and grey for heave (*y*-axis). The *x*-axis of the graph illustrates the 201 measurements recorded during the burst, that is, one measurement during the GPS fix and 200 after that. Eurasian Jay (*Garrulus glandarius*) fitted with a 5 g ICARUS tag (b, Photo: J. F. Masello), and (d) subsequent tracking at the Marburg Open Forest in 2021. Background map in (d): OpenStreetMap contributors (2023).

monitoring (Figure 5; Höchst et al., 2022). Edge AI refers to AI computations performed on the device where the data is collected, rather than at a centralized computing facility.

Bird@Edge utilizes multiple microphones based on the ESP32 microcontroller unit to stream audio to a station, where bird species recognition takes place (Figure 6). The recognition results of different stations are transmitted to a backend cloud server for further analysis by biodiversity researchers. A deep neural network based on the EfficientNet-B3 architecture was trained and optimized for execution on embedded edge devices and deployed on NVIDIA Jetson Nano stations using the DeepStream SDK. During an experimental evaluation in 2022, we found that our system reaches a recognition quality of up to 95.2% mean average precision on soundscape recordings in the Marburg Open Forest (Höchst et al., 2022).

Bat species in audio recordings

Bats are the most geographically dispersed taxonomic group among terrestrial mammals. Excluding the Arctic, Antarctic, and a few isolated islands, all regions of the earth are inhabited by bats (Kunz, 1982). With almost 1400 recognized taxa, bats represent almost one-fifth of the mammalian diversity (Frick et al., 2020). Unfortunately, about one-third of all bat species are classified as threatened or data deficient by the International Union for Conservation of Nature (IUCN), and evidence suggests that approximately half of all bat species are experiencing population declines, or have an unknown population trajectory (Frick et al., 2020). To monitor populations of bat species and thus, biodiversity at scale, automatic bat echolocation call detection and bat species recognition approaches are required.

To address this need, we developed a new approach (Bellafkir et al., 2022, Figure 7) for detecting bat echolocation calls and recognizing bat species in audio spectrograms. Our method uses pre-trained data-efficient image transformer models that are used as components in a workflow we designed for processing audio spectrograms of recorded bat echolocation calls. The workflow consists of two phases: In the first phase, the recordings are scanned in a sliding window approach to localize echolocation calls. In the second phase, the detected calls are classified and assigned to the corresponding bat species. We have shown that our method outperforms state-of-the-art CNN approaches for detecting bat calls and recognizing bat species in several publicly available datasets

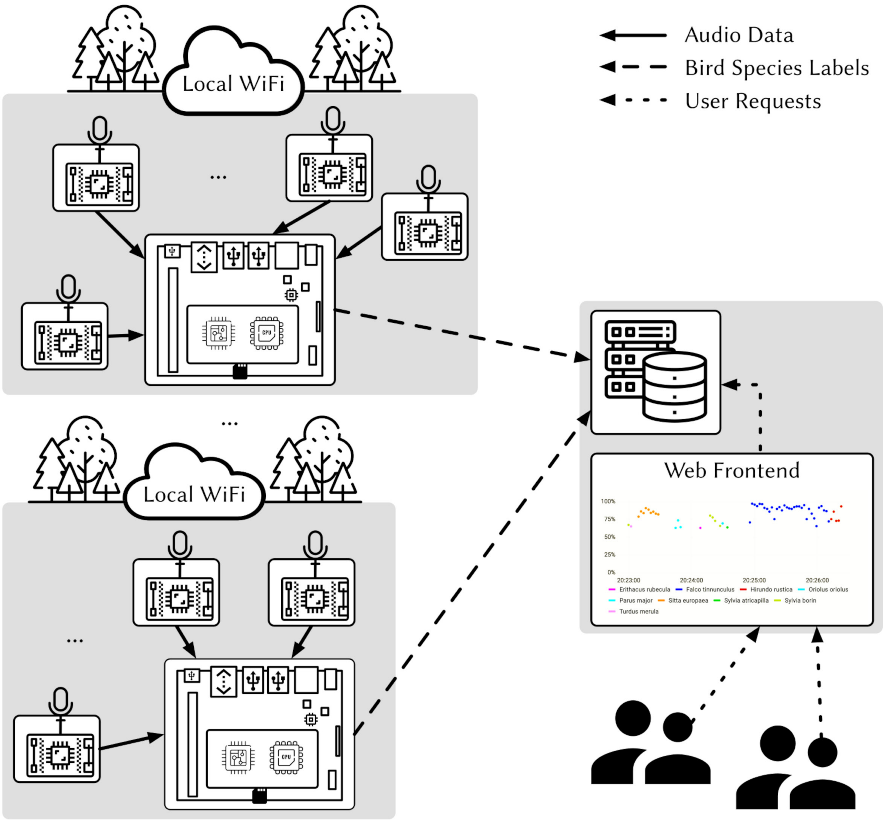

FIGURE 5 Conceptual framework of Bird@Edge. Bird@Edge uses audio recorders and Artificial Intelligence (AI) to detect the diversity of bird species. It comprises multiple microphone units that stream audio to their respective station which performs AI-mediated bird species recognition. The results are transmitted to a backend cloud server, where they can be accessed and analysed through a web frontend.

while achieving an average accuracy of up to 90.2% for detection and up to 88.7% mean average precision for recognition (Bellafkir et al., 2022).

To further improve detection and recognition performance and enable bat behaviour recognition in audio recordings, we applied an object detection model to our spectrograms (Vogelbacher et al., 2023). In addition to species recognition from echolocation calls, our model is able to categorize bat calls into three call types based on behavior: echolocation call, feeding buzz, and social call, with a mean average precision of 98.4%, 98.3%, and 95.6%, respectively.

Wildlife species in camera trap images

Camera traps, first introduced in 1956 (Gysel & Davis, 1956), have contributed greatly to wildlife ecology in recent decades (O'Connell et al., 2011). These heat or motion activated cameras are placed in the wild to automatically record photos and/or videos of animals over a period of time, without the species in focus being disturbed by the presence of humans. Due to the quantity of data generated, manual analysis by experts is prohibitively expensive and time consuming, thus it is desirable to automate this process (Schneider et al., 2020).

In the Nature 4.0 project, we used camera traps to record photos and videos in the Marburg Open Forest over several years. We implemented a two-stage process using AI to analyse the data. In the first step, to localize the animals in the images and to filter out empty images, we used Microsoft's MegaDetector software (https://github.com/microsoft/CameraTraps). MegaDetector is an object detection model, which has been trained with a very large number of camera trap images captured worldwide, and therefore achieves very good animal detection rates, even under poor visibility conditions.

To identify the animal species, we trained a custom classification model based on an EfficientNetV2 network (Tan & Le, 2021). Training images were obtained from freely available datasets of camera trap images from Europe and North America along with wildlife photos from websites such as iNaturalist (https://www.inaturalist.org). The trained model achieved around 87% mean average precision on a validation dataset consisting of a withheld subset from the same sources. We successfully applied the model in the analysis of the images and videos recorded in the Marburg Open Forest (Figure 8), where it achieved 93.88% mean average precision on a manually labelled subset (Schneider et al., 2023).

Insects with automated camera light traps

Reports of insect decline highlight the need for extensive, continuous, and fine-grained monitoring (Didham et al., 2020; Engelhardt et al., 2022; Hallmann et al., 2017). The number of sampling sites is not only limited by personnel, maintenance, and post-processing costs, but also by ethical considerations. Even inventories of moths, which—due to their high diversity and close ties to the environment—are one of the most continuously and intensively monitored insect groups (Fox, 2013), are not extensive enough to provide the information necessary for effective conservation work (Sánchez-Fernández et al., 2021). In recent years, the rapid development of non-lethal, automated moth traps to address these issues became apparent (Bjerge et al., 2021).

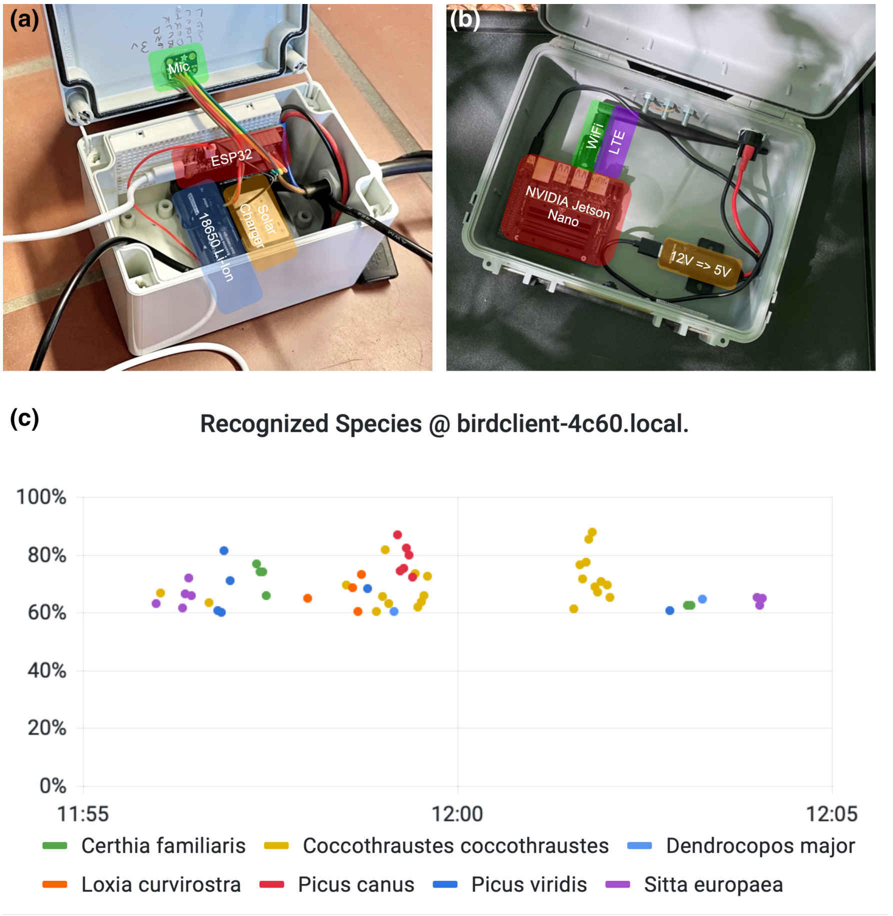

FIGURE 6 Hard- and software solutions of Bird@Edge. Bird@Edge consists of multiple microphone units (a, b) that stream audio to their respective station which performs artificial intelligence-mediated bird species recognition. The results are transmitted to a backend cloud server and can be accessed and analysed through a web frontend. In this example, the frontend shows recognized bird species recorded by a single Bird@Edge microphone (c; *x*-axis: clock time, *y*-axis: recognition confidence).

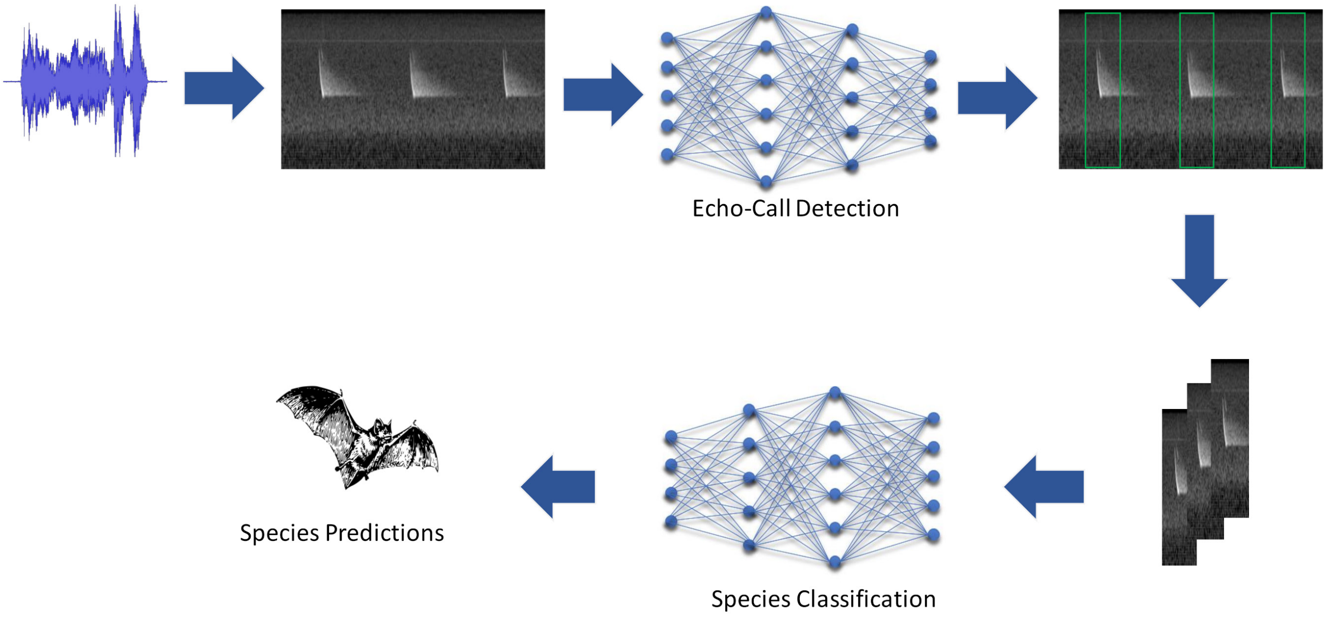

FIGURE 7 Bat species detection and recognition pipeline. The workflow of our approach comprises two phases: In the first phase, a recording is scanned to localize the echolocation calls using a deep neural network. In the second phase, the detected calls are classified and assigned to the corresponding bat species using another deep neural network.

In the Nature 4.0 project, we developed several low-cost automated moth traps as tools for monitoring moth abundance (Mielke Möglich et al., 2023; Figure 9). Our automated moth trap is built from off-the-shelf components, which are powered by batteries or solar panels. The device has a sensor box at its core, containing a camera operated by a Raspberry Pi and a flashlight for illuminated

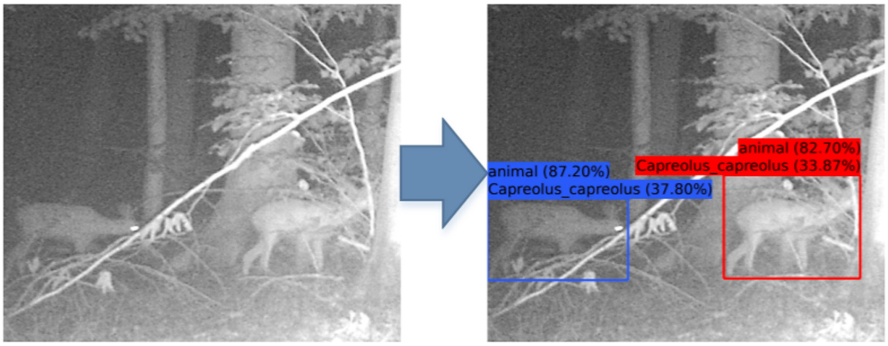

FIGURE 8 Animal detection in camera trap images. The images are automatically analysed by the AI models, first detecting the location of animals in the image and then classifying the species for that area. Here: Roe deer (*Capreolus capreolus*). Photo: recorded by a camera trap in the Marburg Open Forest.

FIGURE 9 Insect monitoring. Automated moth trap for monitoring insect abundance by capturing photos of attracted moths via UV-light. Photo: L. Heidrich.

photos. UV-light is used to attract moths to the LED board opposite to the camera as a standardized resting place. The modular setup allows for the exchangeability of components, such as hardware upgrades, and the software implementation allows for customizable light schedules. Metadata are stored in YAML files. Furthermore, autonomous monitoring of moths over long periods of time is feasible. Our automated moth traps elucidate seasonal abundance trends and provide high-quality training data for neural networks. This proof-of-concept also set the foundation for integrating automated AI-powered species recognition and trait measurements in future design builds. The precise information about the temporal activity of moths, customizable light schedules, and non-lethal method of capturing individuals provides opportunities for further implementation in other areas of research, such as movement ecology.

Insects with radar

The looming prospect of 40% of insect species becoming extinct over the next few decades (Leather, 2018) due to the extensive use of pesticides, intensive land use, and climate change (Groom et al., 2006) necessitates new concepts for autonomous and high-resolution entomological monitoring. A recent review of the current state of insect monitoring by Noskov, Bendix, et al. (2021) demonstrates insect radar solutions to be a suitable option for future real-time monitoring. Modern compact frequency-modulated continuous-wave radar units have shown potential to solve one of the main specific challenges inherent to insect monitoring, namely, observing insects on low flight paths near the ground. Such measurements have not previously been possible with conventional vertically pointing radar systems due to blind spots at altitudes lower than 150 m (Chapman et al., 2002).

We have developed a novel insect radar setup based on a compact frequency-modulated continuous-wave radar module, which was originally developed for autonomous driving applications. Noskov, Achilles, et al. (2021) introduced the proposed radar system, demonstrated its viability, and summarized multiple laboratory experiments. Insect detection and biomass estimation were achieved with a tailor-made mathematical approach. The conducted lab experiments have confirmed the efficacy of our solution. In addition, a light trap was installed for initial testing of the data collected by the radar component. The setup has been evaluated under field conditions in the Marburg Open Forest. A compact autonomous sensor box has been designed for the entire system and successfully used in the forest during all rain-free days (Figure 10). A field campaign conducted by Noskov et al. (2023) demonstrated the suitability of this novel system in a forest environment. A major advantage of this system is that it is much smaller and more cost effective compared to conventional vertically pointing devices, which require a cable to remain powered and housing for the processing unit (Chapman et al., 2002). In contrast, our solution can be used as a mobile device. This novel functionality enabled it to be mounted to our rover platform (see section "A multisensor rover platform") to collect spatial data of low flying insects at multiple positions in the forest.

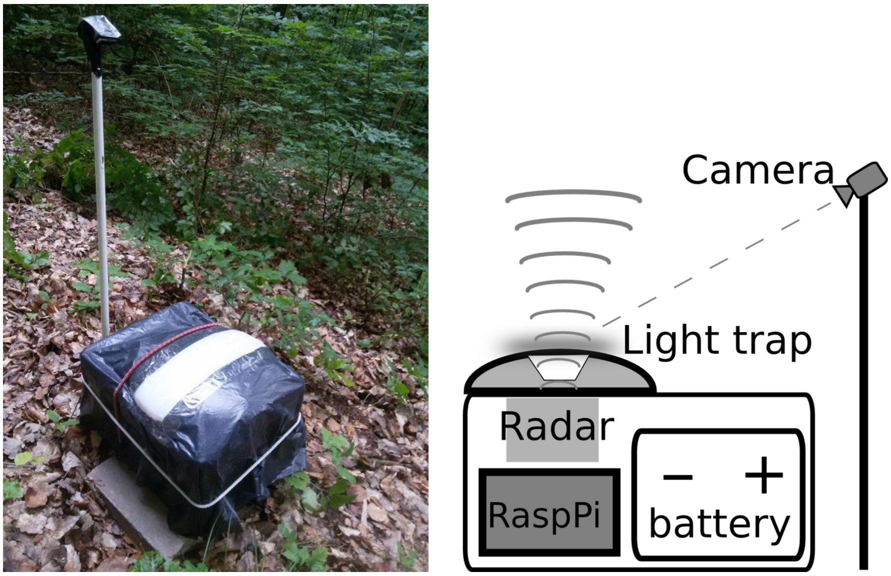

FIGURE 10 Insect radar box. Left: An autonomous compact insect radar box in operation equipped with a light trap and a camera for collecting ground-truth information. Right: Schematic illustration of the insect radar box. Photo: A. Noskov.

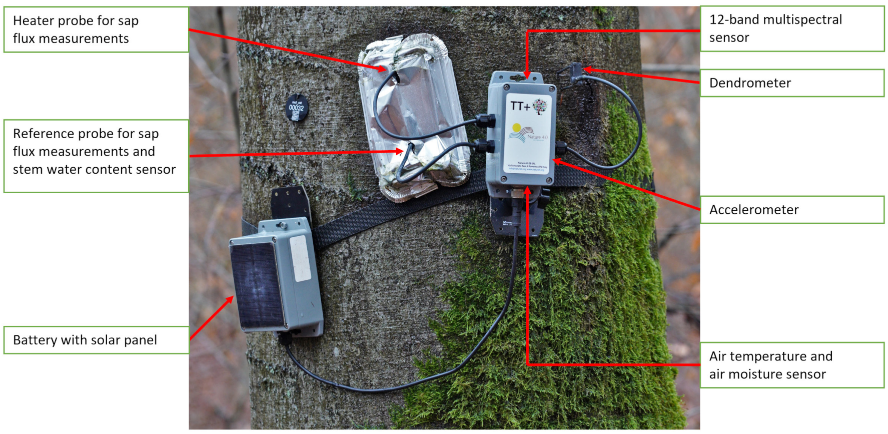

FIGURE 11 TreeTalker mounted on a beech tree. Sensors and other components of the TreeTalker tree monitoring system. Photo: M. Leberecht.

2.1.3 | Measuring

Monitoring trees with TreeTalkers

Networked tree sensors record and transmit information on physiological processes at the individual tree level along with environmental parameters. A general trade-off inherent to the design of such devices is the quality of the sensors, which affects the accuracy of measurements versus cost effectiveness, which affects the possibility of large-scale deployment. In the Nature 4.0 project, we followed a massive deployment philosophy with the mindset of tracking ecosystem responses using trees as sensors themselves, instead of having highly accurate measurements of just a few trees. In the Marburg Open Forest, we have been piloting such a sensor network comprised of 59 TreeTalkers (Valentini et al., 2019) distributed across ~120 ha since spring 2020, achieving a relatively dense coverage of one TreeTalker every 2 ha.

The TreeTalkers function like an Internet of Things (IoT) device, and combine multiple sensors around an ATMega328P 8-bit microcontroller (Figure 11). The water status of the trees is captured by a classic Granier-type sap flux sensor (±0.1°C) and a capacitive sensor for stem humidity (Asgharinia et al., 2022). Incremental growth was estimated by an infrared dendrometer (±100 μm). An accelerometer (±0.001°) allows the detection of tree stem movements for analysis of local wind loads. A 12-band multispectral sensor directed into the canopy was used to calculate vegetation indices. Additionally, air temperature (±0.1°C) and air humidity (±2%) were measured. A full set of measurements is recorded hourly and transmitted via our long range wide area network (LoRa, see Section 2.7) to a gateway. All backups of the data were stored on internal flash memory devices. In the configuration used in the Nature 4.0 project, the TreeTalkers' solar panel-supported Li-ion batteries provide power for 6 weeks of operation, including power consumed for sap flux measurements.

A reference network for high-accuracy positioning in forests

A well-known limitation of the global navigation satellite system (GNSS) is that it is often impossible to obtain accurate coordinates within forests (Pirti et al., 2010). Thus, obtaining accurate positioning data in forests remains a challenge. As one consequence recurrent point clouds obtained by cameras mounted on an Unmanned Aircraft System (UAS) for monitoring trees require their position to be adjusted repeatedly due to the low accuracy of the registered coordinates by the UAS and location problems due to the different

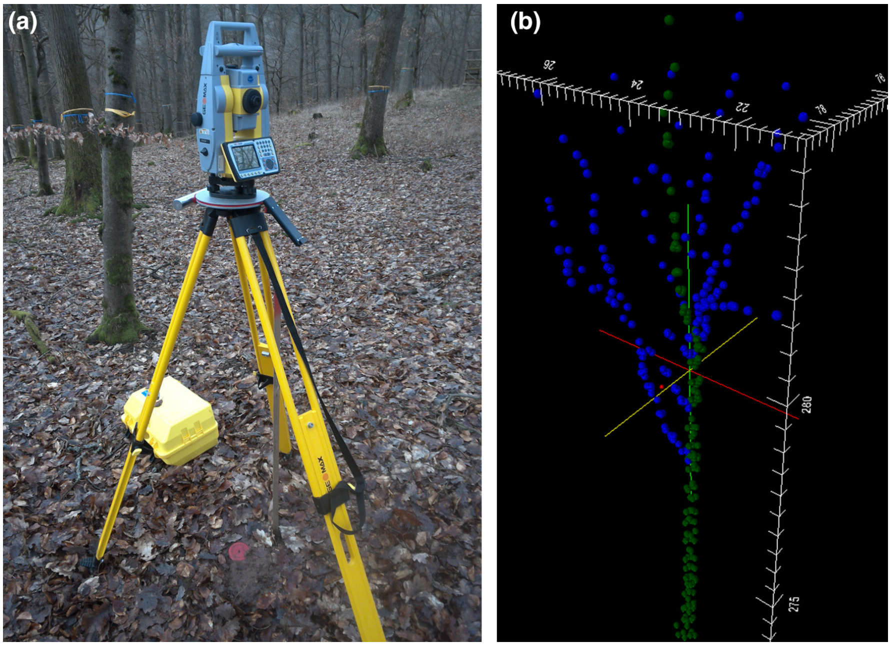

FIGURE 12 Reference network. We created a reference network for high-accuracy positioning in forests. (a) Surveying with the global navigation satellite system (GNSS) and a total station for establishing a reference network and tree measuring. (b) Example of a measured tree with 2 cm accuracy (green points—stem, blue points—main branches). Photo: A. Noskov.

observation geometries used. Without accurate positioning data, it is impossible to meaningfully compare different point clouds and derived products from individual trees. To provide a good baseline for subsequent accuracy corrections, all trees of interest within the Marburg Open Forest were measured with a total station (Figure 12a). A total station is an optical-electronic surveying instrument used to calculate angles and distances.

In the Nature 4.0 project, we first established high-accuracy reference points in two meadow areas close to the areas of interest. We then used the total station to obtain multiple reference points (37 installed survey marks) in the forest enabling us to reach an accuracy of 2 cm. Finally, the main structure of the trees (stem and main branches; Figure 12b) was measured with the total station using at least three reference points. Additionally, the total station was also used to measure the accurate position of other sensors. This for instance enabled us to install a sensor at the exact same place after the winter break, and thus to seamlessly integrate our new data with the previous data. Furthermore, rover tracks (see section below) were measured accurately using the total station. For this, the rover was equipped with a 360-degree prism allowing an accurate definition of the rover's position with coordinates that were automatically recorded during each journey.

A multisensor rover platform

While UASs remain very popular in forest monitoring (González-Jaramillo et al., 2019), rovers also show promise in this field as they have several advantages (Muthulakshmi et al., 2022; Niu et al., 2020). In the Nature 4.0 project, using a rover was beneficial as it enabled us to deploy multiple sensors for a variety of functions, including microclimate measurements and enabling accurate low-viewpoint large-scale mapping of the forest with camera sensors (Figure 13). Our rover can carry relatively heavy sensors such as the insect radar and has good manoeuvrability in forested areas.

FIGURE 13 Multisensor rover platform. Rover equipped with multiple sensors and a prism for tracking by a robotic total station. Photo: M. Dobbermann.

With the insect radar mounted, it can collect spatial information on low flying insects. However, using the rover as a mobile platform required automatic navigation. Therefore, we developed a simple mark-based navigation approach to support low insect flight research in the future. Currently, we use a prism attached to the rover allowing visual tracking of a robotic total station while recording coordinates of the rover automatically at short intervals with very high accuracy of about 1 cm. In addition to the insect radar, the rover was equipped with several other sensors, such as rpLiDAR (for navigation and trees position mapping), both infrared and RGB global shutter cameras (for navigation and vegetation information acquisition), sky-oriented cameras (for tree crown monitoring from the ground) with flashlights (for catching insects), microphones (for forest soundscape mapping), ground-oriented back cameras sensitive to infrared (NoIR), and thermal sensors (thermal camera and infrared thermometer) for forest floor measurements. In the field campaign outlined in Noskov et al. (2023), they sought to monitor forest phenology with a rover they designed, and confirmed the efficacy of this proposed multisensory system in the forest. Adoption of the visual tracking mechanism, and utilization of the Raspberry Pi-based computation module enables simultaneous, real-time, and high-accuracy positioning of observed objects.

One of the use cases still in progress in the Nature 4.0 project is accurate large-scale surface temperature mapping, which will provide micro niche conditions that are important for soil mesofauna and microbes. For these tasks, it was sometimes necessary to navigate the rover manually with a wireless controller. On its way through the forest, the rover can also collect information from multiple permanently installed sensors (such as the TreeTalkers) as an automatic way of data harvesting if no LoRa coverage is available.

2.1.4 | Sensing

Spaceborne and airborne remote sensing

Spaceborne and airborne remote sensing data are highly valuable for biodiversity monitoring (Turner et al., 2015). They provide cost-effective, efficient, and non-invasive means to collect data about the Earth's surface. Remote sensing data provide information at different spatial and temporal scales and can facilitate monitoring of remote or inaccessible areas that would otherwise be difficult to access through traditional field work methods, thus allowing for a more complete understanding of biodiversity patterns and trends (Pettorelli et al., 2014, 2016). Due to the variety of spectral, temporal, spatial resolutions, and the differences in data quality between the various remote sensing platforms, they can be used to monitor biodiversity from the individual species level to full ecosystems, and depending on which level of detail is necessary for the biodiversity monitoring task, different platforms can be chosen for use.

UASs offer a cost-effective means of acquiring remote sensing data, with the possibility of generating temporally fine scale time series. However, their use requires the presence of an operator in the field, and UASs are susceptible to inaccurate georeferencing, as well as shadow and light effects.

Aeroplane remote sensing is more expensive than UAS-based remote sensing, but it often provides higher-quality images, such as Digital Orthophotos (DOPs), which are created by correcting for distortion in aerial photographs. DOPs typically cover large areas at high spatial resolution (~20 cm), but their temporal resolution is low, with public authorities acquiring only one image every 2 years for the Marburg Open Forest. Aeroplanes are also used for large-scale LiDAR campaigns, thereby providing valuable information about the three-dimensional structure of forested areas.

Satellite remote sensing is extensively used due to its comprehensive spatial coverage, high temporal resolution, and medium spatial resolution. Furthermore, satellite remote sensing data is often freely available from organizations such as NASA and ESA. Although they lack the flexible temporal resolution of UASs, they are more stable, providing high-quality data, often at multispectral resolutions.

In the Nature 4.0 project, we used multispectral satellite images with a spatial resolution of 10 m from the Sentinel-2 satellites, data from a UAS time series campaign flown during the vegetation period with a temporal resolution of 1–2 weeks, and LiDAR data (Figure 14). We also used DOPs provided by the local authorities (Hessian Agency for Nature Conservation, Environment, and Geology, HLNUG). These spaceborne and airborne remote sensing data were used to upscale data acquired with the sensor network in the field (see Section 2.8). In the context of large-scale projects involving extensive data collection, the importance of efficient data and metadata management cannot be overstated. In particular, when working with very large datasets, such as ones containing spectral data, utilizing file formats like Cloud Optimized GeoTIFF with SpatioTemporal Asset Catalog metadata becomes the eminently practical choice.

2.2 | Public participation

Global change and ecological collapse are some of the defining challenges of this generation, and to tackle these challenges will require widespread support and awareness from the general public (Intergovernmental Panel on Climate Change, 2021; International Union for Conservation of Nature, 2020). This is particularly true where our fragile forest ecosystems are concerned, and where wider public awareness needs to be created. Education for sustainable development addresses these challenges and helps to foster awareness of the scientific approaches and contemporary technology, which is necessary to identify and discuss the possible future of human-environment interactions (UNESCO, 2020). This challenge is addressed by the SENSO-Trail in the Marburg Open Forest (Figure 15).

The SENSO-Trail was designed for students and upper secondary school pupils and consists of six stations: (1) the observation of an individuum through the example of the physiology of a single tree, (2) the lifeless environment through the example of microclimates, (3) the role of the tree as a habitat and its interaction with wildlife as a microcosm of the living environment, (4) the application of machine learning methods, and (5) remote sensing. It ends with the modelling of forest ecosystems in a societal context with a concrete application reference, such as the development of digital environmental models.

The SENSO-Trail uses a multi-perspective approach (Schmayl, 1995) to break down the content complexity of the Nature 4.0 project, raise awareness, and promote subject-specific knowledge and scientific literacy (Bengel & Peter, 2023). Datasets from the Nature 4.0 project can be accessed in the SENSO-Trail and individual reflection is used to contextualize the learning experience. If the user develops an appreciation for the complexity of natural systems, and an expanded understanding of the biotic and abiotic environment at different scales, each with their own spatiotemporal relationships,

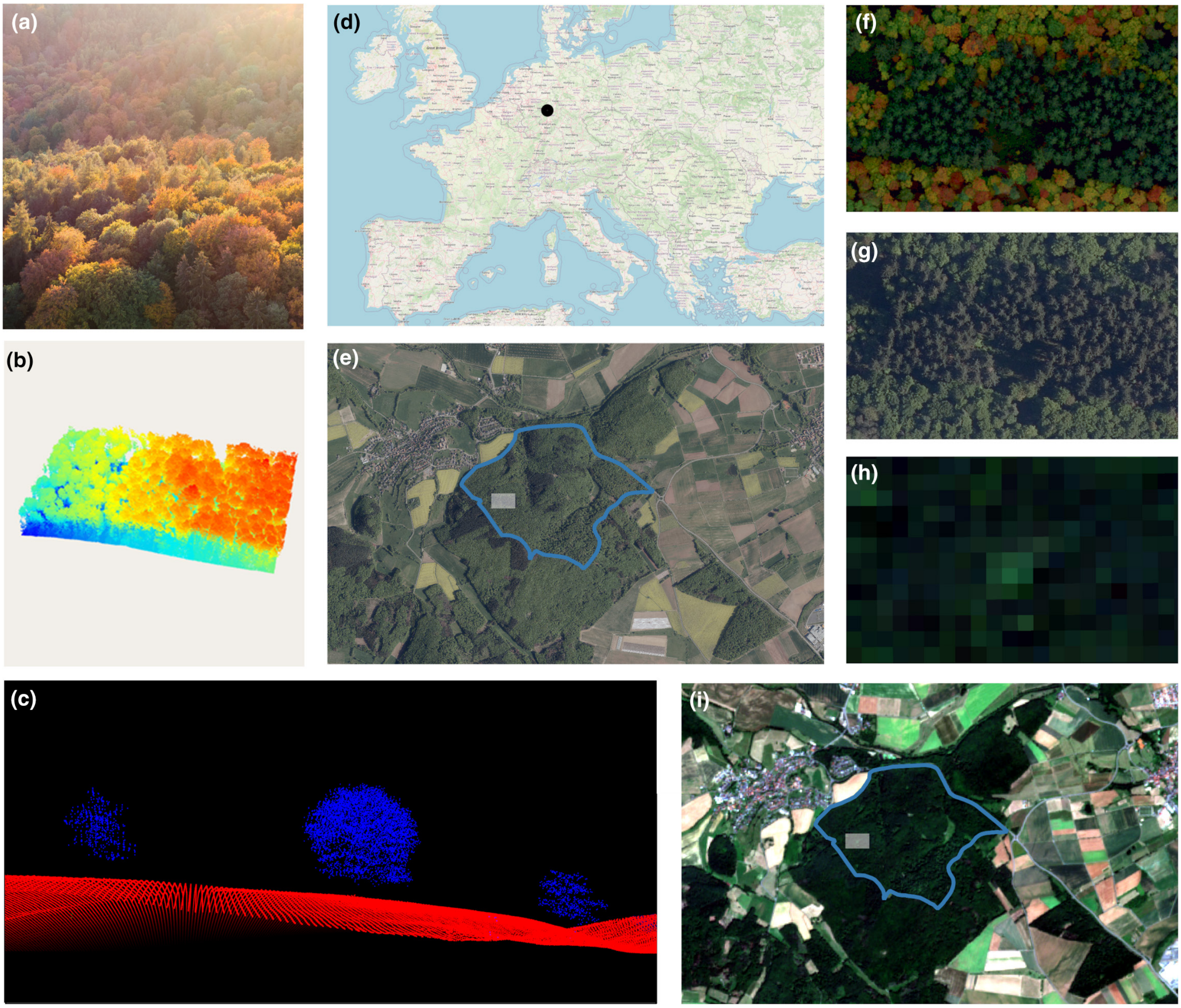

FIGURE 14 Spaceborne and airborne remote sensing in the Marburg Open Forest. Satellite, aeroplane, and unmanned aircraft system (UAS) data were obtained for the Marburg Open Forest in addition to the data collected by the sensor system on the ground for upscaling the field data to area-wide maps. (a) Canopy image obtained with a UAS. Photo: S. Egli. (b) Visualization of a three-dimensional point cloud recorded with LiDAR. Data: Hessian Agency for Nature Conservation, Environment, and Geology (HLNUG). (c) A visualization of a three-dimensional point cloud at single tree level based on LiDAR data. Data: HLNUG. (d) Location of the Marburg Open Forest in Europe shown as a black dot. Data: OpenStreetMap contributors (2023). (e) RGB composite of the Marburg Open Forest (outlined in blue) of a digital orthophoto recorded by aeroplane. Data: HLNUG. White areas in (e) and (i) show the section on which panels (b) and (f–h) respectively have zoomed in on. (f) RGB composite of an image obtained with a UAS. Data: The Nature 4.0 project. (g) RGB composite of a digital orthophoto recorded by aeroplane. Data: HLNUG. (h) Sentinel-2 RGB composite with a spatial resolution of 10 m of the same area as images (f) and (g). Data: ESA. (i) The Marburg Open Forest (outlined in blue) in an RGB composite of a Sentinel-2 scene with 10 m spatial resolution. Data: ESA.

then the goals of project participation will be met (DGfG, 2021; Friess et al., 2020; UNESCO, 2020).

The SENSO-Trail is intended for use in education about sustainable development, and it is designed as a mobile digital-game-based learning approach with a non-linear, modular structure. It can be explored independently by the participants using tablets running the SENSO app. The SENSO-Trail can be explored as a field trip in the real forest or a virtual field trip, SENSO-Trail360 (public demo version: http://85.214.136.59/). The SENSO-Trail was evaluated with pupils aged 15–17 in an intervention study and was found to be an effective and robust tool for learning (Bengel & Peter, 2023).

2.3 | Database systems

We developed four integrated open-source database systems in the Nature 4.0 project, which are tailored to the specific needs of each data type obtained.

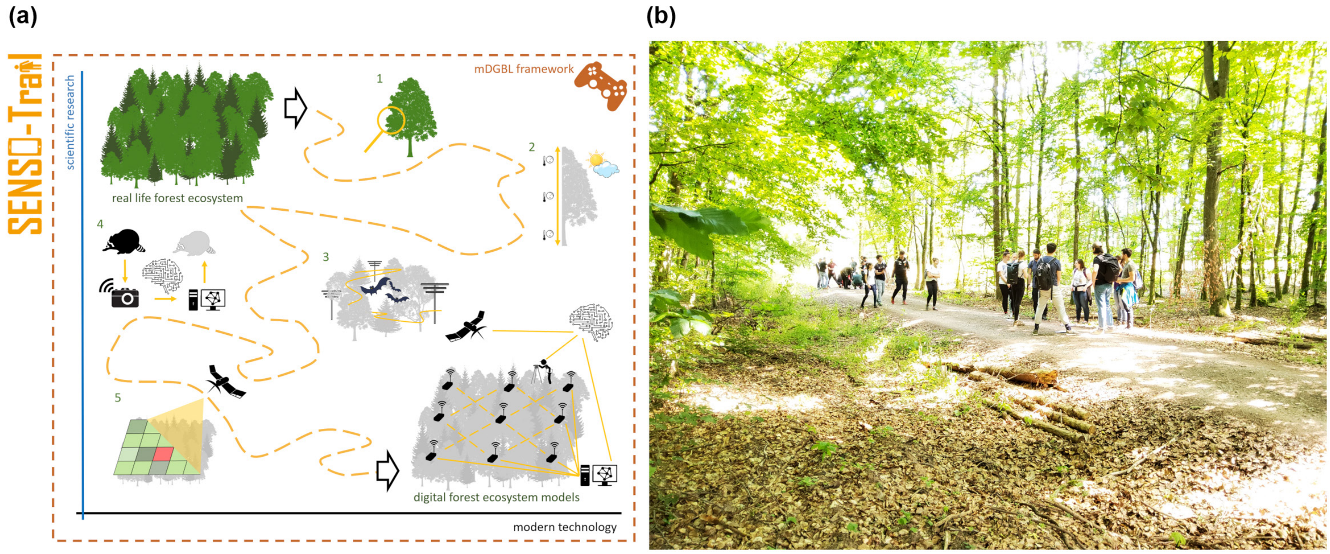

FIGURE 15 SENSO-Trail. (a) Concept chart outlining the contextual framework and integral structures of the educational approach in simplified form. The SENSO-Trail is an educational tool wherein approaches from digital nature trails and mobile digital game-based learning are combined. It was developed both as a real outdoor field trip and as a virtual field trip. The SENSO-Trail aims to raise citizens' and students' awareness of the environmental, scientific, and technological subjects related to the Nature 4.0 project. The SENSO-Trail includes five stations related to the networked sensor system: (1) single tree, (2) microclimate, (3) habitat and wildlife, (4) the application of machine learning methods, and (5) remote sensing. It ends with the modelling of forest ecosystems in a societal context. (b) Students visiting the SENSO-Trail and exploring the Marburg Open Forest. Photo: P. Bengel.

2.3.1 | RSDB

The satellite remote sensing data, as well as the images acquired by UAS flights, are stored in the Remote Sensing Database (RSDB; Wöllauer, Zeuss, Magdon, et al., 2021). RSDB allows for the storage, management, and processing of different types of remote sensing data, such as raster data or LiDAR point cloud data. RSDB can calculate more than 200 biodiversity-related indices based on the stored data.

2.3.2 | TubeDB

To store the data from climate stations and the transmitted TreeTalker data, we developed the Climate Time Series Database (TubeDB; Wöllauer, Zeuss, Hänsel, et al., 2021). TubeDB has low hardware requirements and is simple to install. The raw data collected by the sensors can be stored, quality controlled, and queried. Data from climate stations and TreeTalkers can be loaded and then the time series can be effectively processed. On-demand requests by users, including aggregation by time and gap filling, can be performed in a web browser without the need for much prior knowledge about how to process time series data.

2.3.3 | AudioDB

Audio recordings from AudioMoth devices in the human audible and ultrasonic range are stored in the Nature 4.0 Audio Database (AudioDB; https://github.com/Nature40/audiodb). AudioDB can produce spectrograms, and supports variable playback speed. These help users to label the data for a range of purposes, including machine learning applications. Furthermore, AudioDB produces general measures of the acoustic environment, and is therefore also a robust platform for audio biodiversity monitoring.

2.3.4 | PhotoDB

Utilizing the photo database backend, the PhotoDB of the Nature 4.0 project (https://github.com/Nature40/photodb) manages images produced by devices like wildlife cameras and insect traps. The query function and image sequence view allow users to quickly review large image collections and label individuals (Figure 16).

All our databases provide web interfaces, are easy to install without the need for programming skills, and facilitate the data to be used for scientists of any discipline.

2.4 | Example: Data storage with AudioDB

Audio samples as well as camera and insect trap images should be accompanied by metadata. Some metadata like recording duration or the device's serial number are directly stored in data files by the generating devices. As the data is processed, additional metadata is added and modified. For the sake of efficiency and to preserve the integrity of the original data files we chose an approach to store metadata in separate files. In the first step metadata properties from the original files were extracted and stored in YAML files (https://yaml.org/spec/1.2.2), so that each original file will have a corresponding YAML file. Subsequently, additional metadata was added to the YAML files

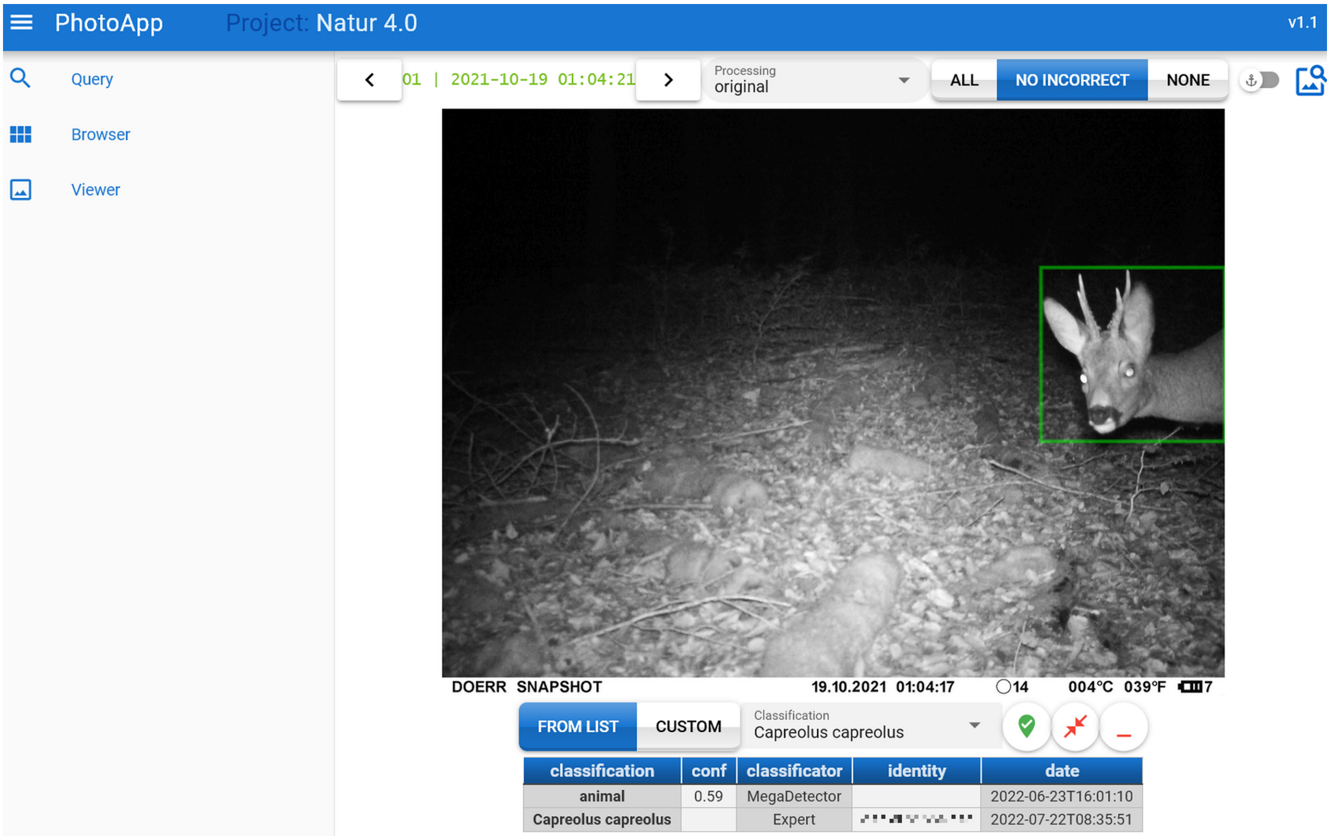

FIGURE 16 PhotoDB. PhotoDB is used for storing, querying, and inspecting images as well as for creating and refining training samples for machine learning applications. The left panel offers users the option to query, browse, and view captured images. The images are displayed in the centre. In these images, animals detected with machine learning can be marked with a green box. Arranged below the image are the label controls and previously saved labels. The labels inferred by machine learning and those assigned by an expert are also displayed here.

as data processing continued. This approach means that metadata is not only accessible to our databases, but also through scripts and by researchers. For example, the location of a recording is essential for data analytics. Furthermore, because recording devices may be spread across the field site, a lookup table can associate device serial numbers and times to locations in AudioDB. With AudioDB, it is also possible to add species labels to the metadata. This can be done with either machine learning scripts or by the users directly. Species labels, location, and time form the basis for monitoring analytics, such as when making a time series of species occurrences (Figure 17).

2.5 | Data integration

To provide a unified overview of the developed database systems and to offer the possibility of combining the internal data from the different databases with external data, we designed integration layers with a consistent data representation. Such a representation of combined datasets allows deeper inferences to be made than each local database alone could support.

Our integration approach employs a previously developed system for visualizing, analysing, and transforming spatiotemporal data (VAT; Authmann et al., 2015; Beilschmidt et al., 2017) and its successor Geo Engine (Beilschmidt et al., 2023), both offer state-of-the-art technology successfully developed in GFBio (Diepenbroek et al., 2014), and were subsequently refined in NFDI4Biodiversity (Glöckner et al., 2019). Geo Engine provides user interfaces to import and export both rasterized and vectorized spatial data, following common data standards (Figure 18). Similar to GIS software, there are multiple layers, each representing a thematic topic. Thus, Geo Engine supports an ad-hoc combination of arbitrary layers and can also calculate many crucial biodiversity indicators as a function of time. Furthermore, due to an easy-to-use web interface, Geo Engine facilitates the creation of powerful workflows for complex computations and visualizations without the need to write any code. These workflows, and the entire map visualization adapt to changes in the spatial and temporal context, that is, the visualization will be redrawn when a user changes the geographic region or the time period.

As Geo Engine is a core component within NFDI4Biodiversity, an additional two future research opportunities appear. Firstly, data from the Nature 4.0 project can be readily shared with the large user community of NFDI4Biodiversity. Secondly, data from NFDI4Biodiversity can be used in the Nature 4.0 project. The synergy created by combining both enables farther reaching inferences to be made in the future.

Geo Engine, for instance, adheres to rigorous metadata standards, ensuring that data imported or exported to it retains its

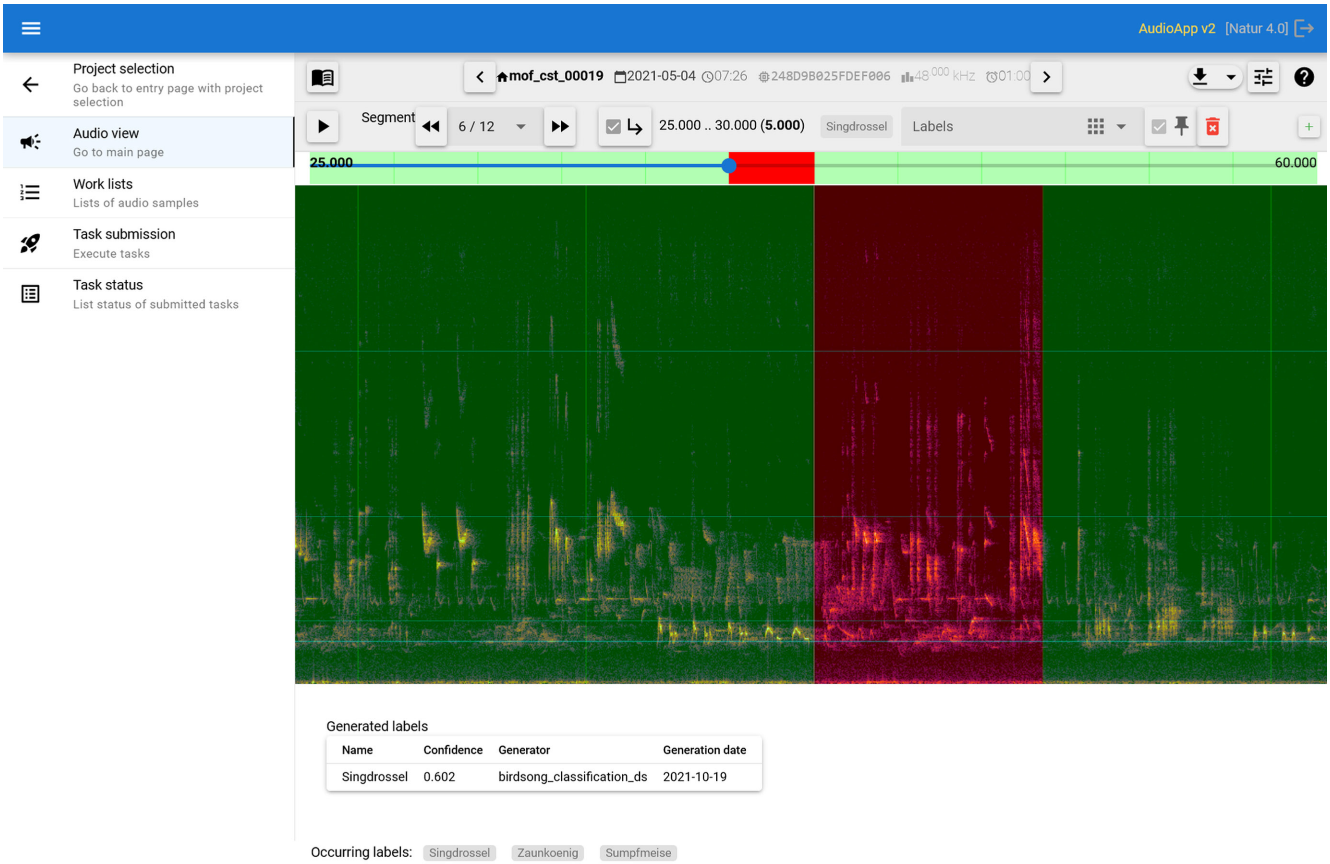

FIGURE 17 AudioDB. When reviewing sequences of audio samples in AudioDB, specific criteria can be selected, such as detected species which are not typically present in that location. This figure shows the web view of AudioDB. On the left panel, the "Audio view" button can be selected to display a spectrogram of the recorded audio. On the top bar, the audio sample selector lets the user select a recording by location and time. Below that, the current label segment is selected and labelling controls are provided. On the central panel, the audio sample is visualized by a spectrogram. Above the spectrogram the green bar represents the timeline, including a segment of the timeline in red, which has also highlighted in red the corresponding segment of the spectrogram below. At the bottom, the saved label of the selected audio segment is presented. Within this view, species in audio samples can be manually labelled, and machine generated labels can be reviewed.

contextual relevance and can be seamlessly integrated with other platforms. The use of standardized metadata formats, for example, saved in YAML files as in AudioDB (see Section 2.4), RSDB, and TubeDB further ensures that any Nature 4.0 data integrated into other projects, or integrated into the Nature 4.0 project from Geo Engine remains consistent, discoverable, and readily understandable. Furthermore, there are R packages available for accessing our databases (rTubeDB, https://github.com/environmentalinformatics-marburg/tubedb/tree/master/rTubeDB; RSDB, https://github.com/environmentalinformatics-marburg/rsdb/tree/master/r-package). Within the R programming environment, R scripts can, for example, aggregate data for analyses, such as climate data from TubeDB and satellite data from climate station locations within the RSDB.

2.6 | Data transformation

In this section, we discuss data transformation in the pre-processing phase when classifying bird songs and bat echolocation calls (see sections "Bird species in soundscapes" and "Bat species in audio recordings").

Bird songs are known to exhibit highly localized time frequencies, that is, there are only a few frequencies contained in a bird song. Therefore, as the main transformation we selected to use the windowed Fourier transform (Gröchenig, 2001) for these two applications, which can be efficiently implemented to generate a spectrogram. Initially, raw spectrograms were used as input data for a classifying CNN (Heuer et al., 2019; Mühling et al., 2020), which already yielded a very high classification rate (up to 96.9%). Subsequently, we began optimal denoizing using thresholding methods followed by compression of the spectrograms for the pre-processing phase (Dahlke et al., 2022).

Compression is important to transmit the data required for such extensive environmental monitoring, which can be particularly useful when processing the recordings on edge devices. Variations of the windowed Fourier transform, such as the alpha-modulation transform, can also detect local singularities (e.g., cracking branches) and are currently being investigated further.

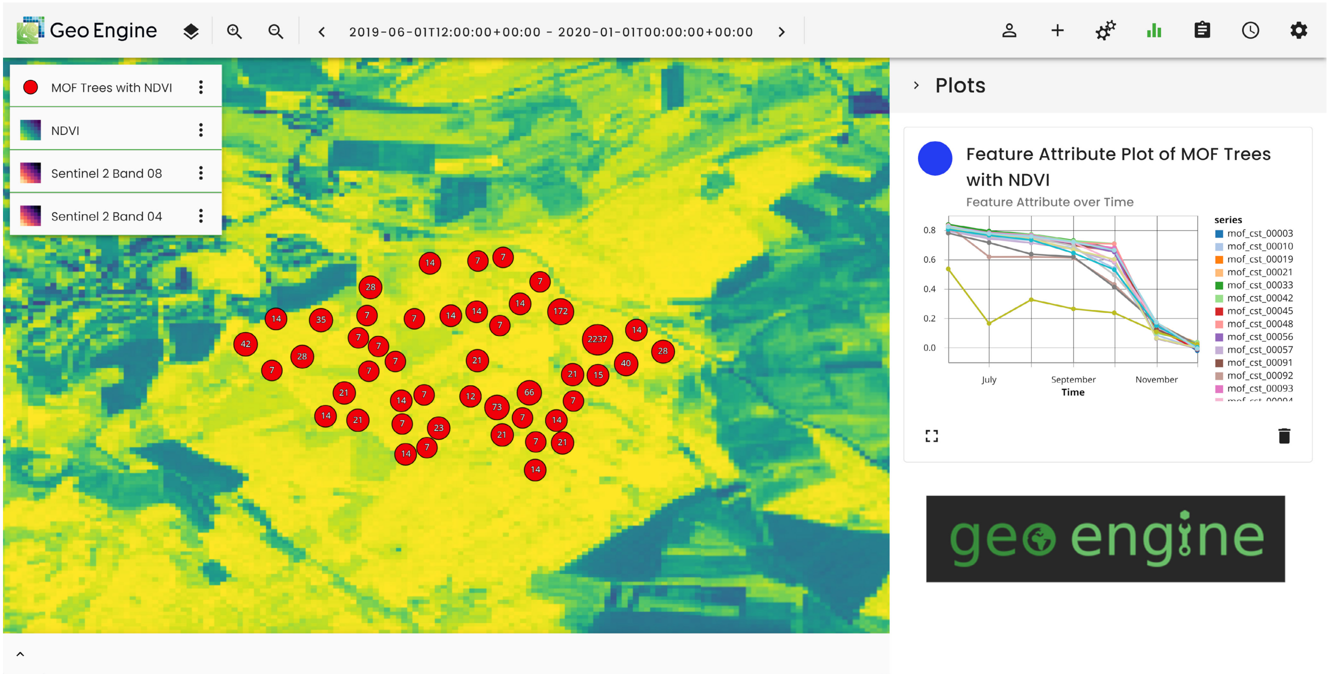

FIGURE 18 Geo Engine. An interactive map visualization of sampled trees in the Nature 4.0 project with supplementary background information. The list of layers is in the upper left corner of the interface. The second layer contains the locations of the trees examined within the Nature 4.0 project. The trees are represented as red dots in the map panel. The background layer displays the Normalized difference vegetation index (NDVI). NDVI is often used to quantitatively assess the greenness of vegetation, and is therefore suitable to determine vegetation density and evaluate changes in plant health. Higher NDVI values indicate a more favourable environment for trees to live in. The NDVI layer is derived from a function of the fourth and eighth bands of the Sentinel 2 data (layers 4 and 5 in the layer list). Additionally, the NDVI values are attached to the trees and the resulting points comprise the first layer. The panel on the right-hand side shows the NDVI of each tree as a function over a user-defined time period.

Here, we included the denoizing step for the spectrogram into the workflow (Figure 19). While the classification performance was not significantly improved, clear and transparent spectrograms may improve the interpretability of algorithms based on spectrograms.

2.7 | Data transmission

A central challenge inherent to transmitting data within the Nature 4.0 project is optimizing transmission protocols across a variety of sensor models, whilst preserving metadata and reproducibility, all while keeping storage space used at a minimum. For example, TreeTalker data are transmitted as plain text. Plain text data can be transmitted in an energy-efficient manner using LoRa to local cloud hubs, through which the collected data are further transmitted to central data servers via the public mobile network (Baumgärtner et al., 2018). More challenging is the transfer of audio and video data due to their format and size. Video and audio recording devices typically generate very large datasets. For example, 15 min of ultrasonic audio recordings per hour, 24 h per day from 48 AudioMoth devices, yielded 5 TB of data every week. It is impractical to wirelessly transfer such large quantities of data from the field to central data servers due to time, battery, and financial constraints. Given these challenges, we opted to reduce the quantity of data recorded.

To reduce the quantity of data to a manageable size, we used event triggers like those found in off-the-shelf wildlife camera traps. However, single device approaches like this often fail to trigger when small or fast-moving animals are being studied. Multi sensor solutions represent a possible solution as one sensor can be used to accurately trigger other sensors in the network. For example, the *BatRack* system in the Nature 4.0 project allows practitioners to obtain energy and data-efficient video recordings of bats because the cameras are only switched on, and the video signal is only recorded, if the ultrasonic device detects bats in the vicinity of the system (Gottwald et al., 2021).

Despite yielding a considerable reduction in the size of data, a substantial quantity is still recorded. These data require an efficient transmission solution, as, especially in areas with a poor internet connection, transmission will continue to be a major challenge in the future (see Section 3). In contrast, the VHF data from animals can be transmitted by the newly developed transmission system *tRackIT* (Gottwald et al., 2019).

2.7.1 | Android app for opportunistic data offloading

The involvement of the public, in citizen science initiatives such as the Senso-Trail, facilitates additional, opportunistic ways to

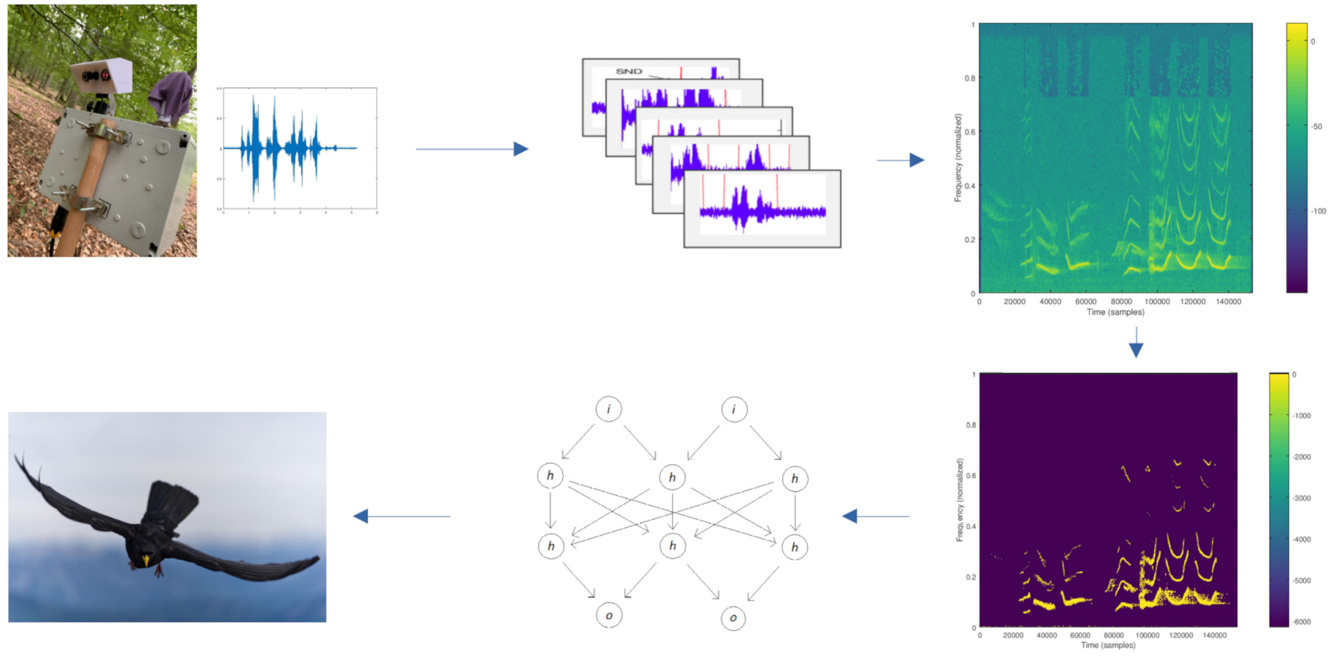

FIGURE 19 Classification workflow: from audio recordings to bird species. Following the acquisition of the raw soundscape via a microphone-equipped sensor box (upper left), we detected sections with bird songs (upper middle). These were transformed into a spectrogram using the Gabor transform, a discretized version of windowed Fourier transform (upper right). The spectrogram was then denoized (lower right) and used as input in our convolutional neural network (lower middle) for the final classification of a bird to the species level (lower left). Photos: P. Lampe, M. Michelsen.

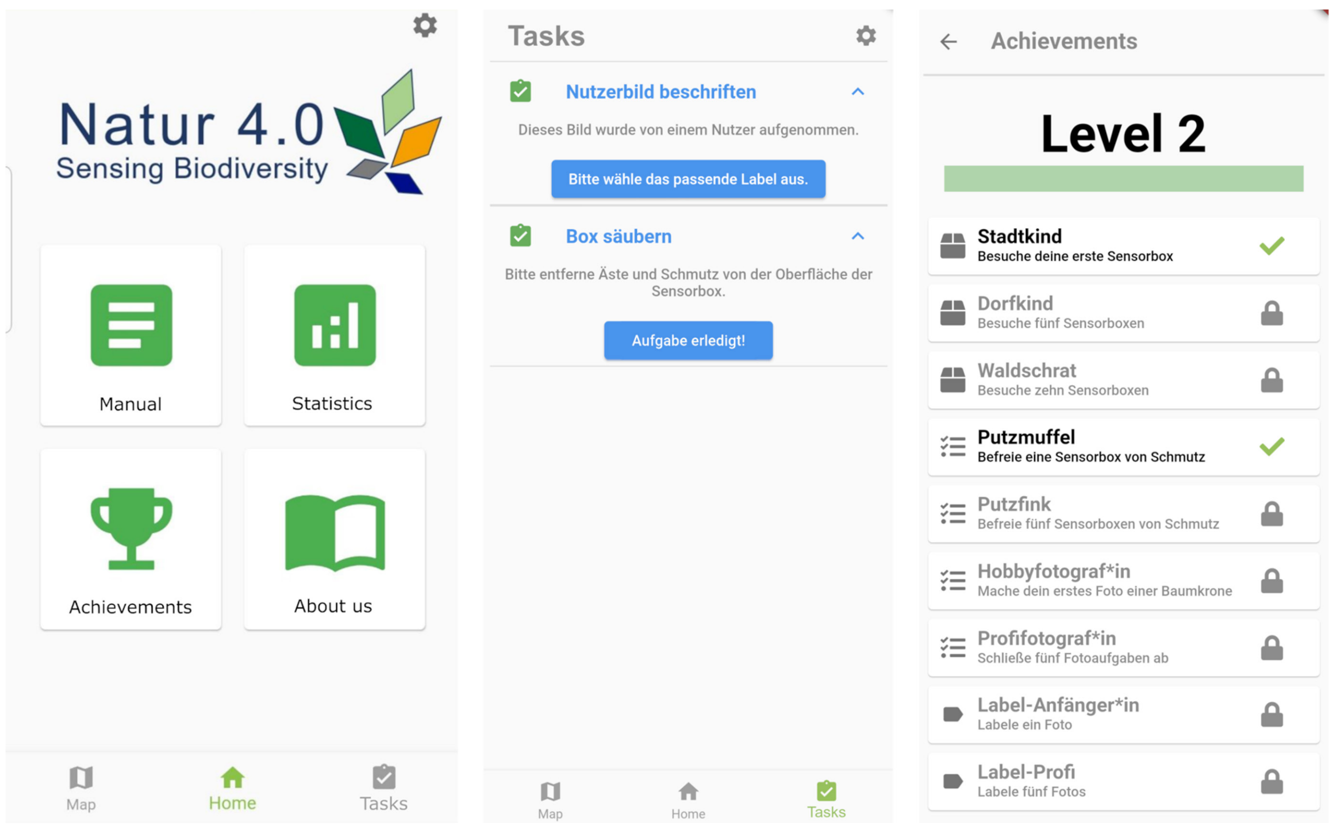

FIGURE 20 Nature 4.0 Sensing Biodiversity App. The Nature 4.0 Sensing Biodiversity app prototype provides information about the project, and the possible interactions of users with the sensor network using their smartphones. Statistics and achievements implement basic gamification features to incentivise tasks (e.g., clearing foliage off a photovoltaic panel).

transport data from our sensors to our storage. This *opportunistic offloading* is especially useful when other communication networks are unavailable, or which simply do not have sufficient capacity to transmit the sensor data. To demonstrate the effectiveness of inviting the public to facilitate the submission of our data, we developed a prototype app for Android smartphones, which allows users to use their phones as "digital data backpacks" whilst in the forest. The app will ask users how much of their device's storage it may use to facilitate data transfer. Whenever a user is within transmission range of a sensor, it will transfer its data to the smartphone. Users simply need to turn on their Wi-Fi, and all further processing is performed in the background. The app also asks the user to select a home network (such as the WLAN at home or university). When the user's device is next connected to their home network, the data will be automatically uploaded to our database. The prototype also showcases possible user interactions with sensor boxes. This may include direct access to currently collected data; or active participation with simple tasks, such as removing foliage from a photovoltaic panel, assigning tags to an image to train machine learning models; or even extending the range of available sensors to the sensor box for a short period of time, such as by taking photos or measuring ambient light with the smartphone. Statistics about user interaction and data offloading can be collected locally on the phone, which brings some basic gamification elements to the user as a possible incentive for long-term involvement. As our team is based in Germany, the app's user interface is written in German to more effectively target the wider German public. However, an English translation is available for some parts of the app (Figure 20).

2.7.2 | Reducing energy consumption

To improve the longevity of mobile sensor devices, such as those mounted on a deer, energy consumption must be reduced. A major influencing factor is the transmission of data to our database. On one hand, transmitting the data over cellular networks is costly and energy inefficient, in addition to the previously described lack of cellular coverage in the forest. On the other hand, short-range transmission, such as over Wi-Fi, requires opportunistic probing for the availability of a gateway (data sink) to the database. Therefore, both the gateway and the mobile sensor node need to have an active Wi-Fi transmitter, which consumes a large amount of energy. As the remote sensors are battery powered, this requirement can severely impair the sensor's longevity once it is deployed in the field. Utilizing GPS or other GNSS signals in order to match a sensor's position against the locations of the gateway is also energy-inefficient.

To reduce the sensors' energy consumption while opportunistically probing for gateway devices, we developed a two-tiered approach using both Wi-Fi and LoRa transmission protocols (Zobel et al., 2021). LoRa is used to probe for gateway availability with its ultra-low power setting. This resulted in a transmission range comparable to that of Wi-Fi in the same environment. The gateway responds on LoRa and the node estimates if a Wi-Fi connection would be possible based on the received signal strength. Only when expected to be suitable, the Wi-Fi modules of both the mobile sensor node and the gateway are turned on. Subsequently, they connect to each other, data is uploaded to the gateway, and the Wi-Fi modules are turned off again. To determine the threshold for suitable connections, we measured the signal strength for Wi-Fi and LoRa in the Marburg Open Forest and correlated them with a successful Wi-Fi connection to upload data afterwards. Our evaluation indicated a similar success rate as a location-based approach using a GPS sensor, but with significantly reduced power consumption (approximately 37% less) when measured with a USB multimeter, due to the omission of the energy-intensive sensor location and always-on Wi-Fi transmitter.

2.7.3 | Opportunistic networking

Particularly in areas with poor infrastructure, such as remote research areas, the transmission of data with conventional cellular networks is not always possible. Opportunistic networks can enable transmission with the participation of researchers and members of the public who are passing through the target area. In this process, data from stationary installations are transmitted to passing nodes, which transfer them through their movement to areas with better network connections and then enter them into databases. In order to use this technology efficiently, the following developments were implemented in the Nature 4.0 project:

We have developed DTN7, which is an open-source implementation of the recently released Bundle Protocol Version 7 (Penning et al., 2019). With its modular design and interchangeable components, DTN7 facilitates Delay-Tolerant Networking (DTN) research and application development. We have also developed a browser-based implementation, which empowers any user with a web browser to participate in a DTN network (Baumgärtner et al., 2019).

A disadvantage of DTN networks is the limitation of the return channel because a server cannot easily request data of a certain type. To compensate for these disadvantages, LoRa connections were used. We have developed an approach to facilitate remote device-to-device communication via smartphones and integrated the LoRa technology into DTN7 (Höchst et al., 2020).

Finally, we developed an approach to allow scenario-specific routing in DTN7, in which a network operator can design a routing algorithm tailored to the scenario where it is deployed by sharing contextual information about both the bundle and the node, and routing decisions can be made using this metadata (Sommer et al., 2022).

2.8 | Area-wide biodiversity mapping

The sensors of the Nature 4.0 network collect very large amounts of data through continuous monitoring, which are subsequently stored in our databases. These databases form the basis for biodiversity monitoring in the Nature 4.0 project. By opting for a continuous monitoring approach, a variety of novel remote sensing possibilities open up. For example: permanently monitoring the drought stress of trees so a monitoring structure that alerts the concerned person before the tree suffers irreversible damage can be set up. In addition, the large datasets stored in our databases serve as training and testing data for remote sensing-based machine learning methods. As not all trees in a forest can be equipped with monitoring devices, it is necessary to upscale the collected data using satellite remote sensing data. This approach could enable forest managers to monitor drought stress across an entire forest.

Satellite observations such as the Sentinel satellite group, GEDI, or the upcoming BIOMASS system, deliver sufficiently high spatial and temporal resolution (tens of metres, <14 days, respectively) so that the sensor records can be upscaled to area-wide datasets. Furthermore, time series anomaly detection enables the creation of an early warning system. For smaller areas, such as the Marburg Open Forest, CubeSat satellites were adequate in addition to large-scale satellite systems such as GEDI, Sentinel, and BIOMASS. The

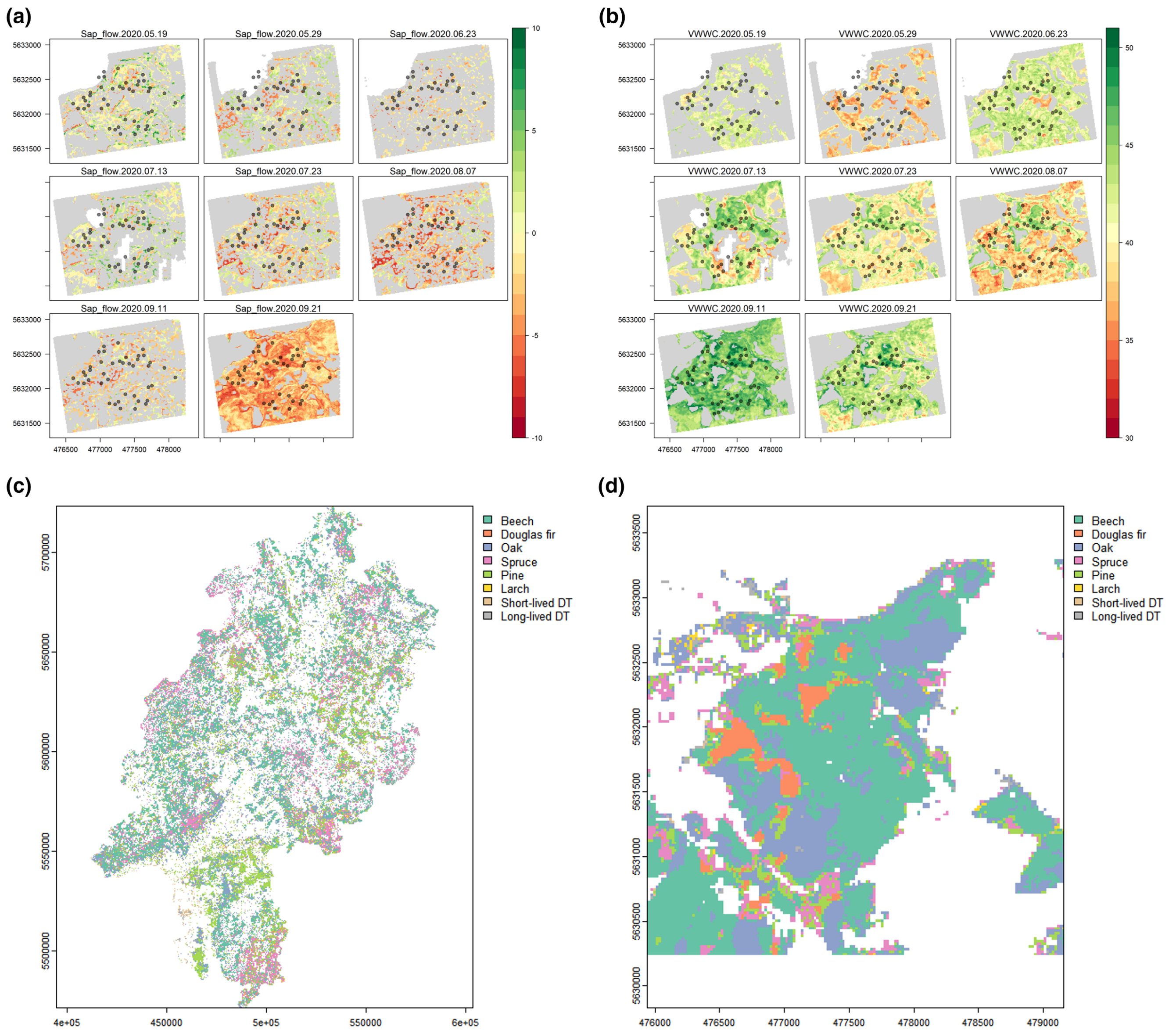

FIGURE 21 Examples of area-wide mapping. Time series mapping of volumetric wood water content (a) and sap flow (b) in the Marburg Open Forest. Grey dots represent the trees that were equipped with TreeTalkers and collected the data used for upscaling. Remote sensing data from Sentinel-2 was used to create these visualizations. Data: ESA. (c, d) Area-wide mapping of eight tree species groups namely beech, Douglas firs, oak, spruce, pine larch, short-lived deciduous trees (short-lived DT), and long-lived deciduous trees (long-lived DT). Each was upscaled using a combination of machine learning methods, Sentinel-2, LiDAR, and forest inventory data for the whole federal state of Hesse in Germany (c), and the Marburg Open Forest (d). Data: ESA, Hessian Agency for Nature Conservation, Environment, and Geology (HLNUG).

combination of these systems with autonomous sensor data is a step towards near real-time biodiversity monitoring.

In addition to near real-time biodiversity monitoring, a comprehensive ecosystem inventory is also necessary to effectively monitor biodiversity. In the Nature 4.0 project, for example, the tree species composition in the Marburg Open Forest and beyond was determined using machine learning methods in order to be able to better assess the forest's suitability as a habitat for different species. This was done using a time series from Sentinel-2 in conjunction with LiDAR data (Figure 21).

The same quantitative methods used to upscale data on tree stands can also be applied to animal models, such as bats. The optimal characteristics of bat habitats are already well understood making bats an ideal model organism for upscaling, as it will be clearer which areas should be designated for protection (Gottwald et al., 2022). Moreover, in the Nature 4.0 project, the species distribution modelling software, spatialMaxent, was developed to create models that consider spatial autocorrelation in the training data (Bald et al., 2023).

3 | CONCLUSIONS

The Nature 4.0 project's modular structure, comprising sensors, data transmission, and data storage, allows for flexibility and scalability in monitoring a wide range of species and ecosystems. By incorporating both static and mobile sensors, the project captured detailed information about species populations, traits, and community compositions that would otherwise be difficult to obtain. The extensive datasets this project has generated were essential for training and testing machine learning models, which were used in conjunction with remote sensing data to monitor and map indirect biodiversity measures.

Nevertheless, to advance networked sensor systems for future integrated biodiversity monitoring, interdisciplinary collaboration will be essential. Our experiences in the Nature 4.0 project have highlighted ten major challenges that need to be addressed to better understand and mitigate the ongoing loss of biodiversity while ensuring the sustainable management of ecosystems and the provision of ecosystem services.

3.1 | Workload and costs

Networked sensor systems for biodiversity monitoring must be cost effective and time efficient. Commercial sensors can be expensive, particularly when used to comprehensively cover large study areas. However, a nascent trend towards using open-source sensors, built from off-the-shelf consumer electronics, continues to provide interesting new possibilities (Baumgärtner et al., 2018). This approach both reduces costs, and also facilitates rapid sensor development while leveraging a wider range of experts' participation. Furthermore, customizable sensor components can be easily exchanged as needed. Cost-efficient sensor systems will allow broader access to technology, enabling biodiversity monitoring in remote and hard-to-reach areas.

3.2 | Energy consumption and storage demands

To enhance the operational lifespan of networked sensor systems that are used for integrated biodiversity monitoring, minimizing energy consumption and storage requirements will be essential. The use of energy-efficient sensors and renewable energy sources, such as solar power, can help reduce energy consumption and operational costs, particularly in remote areas where access to electricity may be limited. Additionally, the implementation of intelligent power management systems, like the camera network developed by Abas et al. (2018), can adapt to the available energy levels, extending the system's lifetime by reducing maintenance requirements. Therefore, incorporating sustainable energy sources and efficient power management modules in networked sensor systems can substantially improve the practicality of biodiversity monitoring in various environments.

3.3 | Data accuracy and quality

Networked sensor systems must generate precise and accurate data for effective and reproducible biodiversity monitoring. Ensuring the accuracy of data collected can be challenging as maintaining sensor calibration, the sensor's sensitivity to environmental conditions, and potential biases introduced by the monitoring methods can all distort the final dataset. Therefore, continuous evaluation and validation of the data through comparisons with in situ field observations or other reliable sources are essential to maintain data quality. An open-source approach can facilitate collaboration and transparency in this process.

3.4 | Positional accuracy

Researchers and practitioners often report difficulties when trying to obtain accurate coordinates using GNSS. To overcome these difficulties, we deployed a reference network using a total station. The total station provided improved positional accuracy, albeit in a relatively small area due to the labour-intensive setup process. In the future, we will explore innovative solutions for enhancing positional accuracy over larger areas, such as the Marburg Open Forest. One potential approach involves utilizing a UAS equipped with an advanced GNSS receiver and prism, which could provide high-accuracy coordinates by communicating with the total station.

3.5 | Artificial intelligence

With the increase in data collection, AI can help to automate the data analysis process with machine and deep learning methods.

However, this will also require an understanding of the biases that can be inherent within the dataset or design of the model being used, and consequently, fair consideration of the ethical implications this raises. Overall, AI will be a valuable tool to improve the accuracy and efficiency of biodiversity monitoring, which will subsequently support more comprehensive biodiversity monitoring.

3.6 | Data privacy and ethical considerations

Deploying networked sensor systems in natural environments raises potential data privacy concerns, particularly if the remote sensors capture image or sound data. Guaranteeing data privacy and addressing ethical considerations are essential to maintain the public's trust towards monitoring programmes, and the development of this technology as a whole. This may involve developing guidelines for responsible data collection, storage, and sharing, in addition to engaging with stakeholders and local communities to address their concerns.

3.7 | Interoperability and standardization

As networked sensor systems continue to advance, the current lack of standardized protocols for data collection, storage, and analysis becomes increasingly limiting. By promoting interoperability across the current variety of sensor systems and data formats, the research community can facilitate the integration of data from diverse sources, which will help to support collaboration and knowledge sharing among researchers and practitioners. Each discipline's scientific community should establish unified standards for metadata to enhance the consistency of data and facilitate collaboration. Standardization also supports the creation of open-source tools and platforms for data processing and analysis, further advancing biodiversity monitoring efforts, while adhering to the FAIR data principles (Wilkinson et al., 2016).

3.8 | Collaboration and knowledge sharing

Collaboration and knowledge sharing across disciplines is vital to disentangle and combat the nuanced factors which lead to biodiversity loss. Developing and implementing networked sensor systems for integrated biodiversity monitoring will require the involvement of experts from various fields, such as ecology, engineering, computer science, and data science. By fostering collaboration and sharing best practices, researchers and practitioners can benefit from diverse perspectives and the latest technical developments, accelerating the advancement of networked sensor technologies and their integration into conservation practice. Furthermore, promoting partnerships between academia, governmental organizations, and non-governmental organizations will naturally bring research, policy, and practice into alignment, thereby enhancing the broader effectiveness of conservation efforts.

3.9 | Public engagement and education

Raising the public's awareness and understanding about the importance of biodiversity conservation, and the power networked sensor systems have to monitor ecosystems will be imperative to build support for monitoring and conservation programmes in the future. Engaging with local communities, stakeholders, and the broader public can help to foster an appreciation for the natural environment, and the exciting technology being used in cutting edge conservation programmes. Through hosting a range of educational programmes, workshops, and outreach activities researchers can highlight the benefits of networked sensor systems, demonstrate their practical applications, and encourage public participation through citizen science initiatives. By actively involving the public in biodiversity monitoring efforts, and nurturing an attitude towards stewardship of the natural environment, networked sensor systems can contribute to better informed and collaborative conservation strategies, which will lead to better outcomes for ecosystems, and the species that inhabit them.

3.10 | Real-time data processing

As networked sensor systems generate vast amounts of data from the many sensors in the field, the ability to process and analyse this data in real-time becomes increasingly important. Real-time data processing can enable timely identification of emerging trends or threats to biodiversity, allowing for more rapid and effective conservation actions. However, achieving real-time data processing requires the development of new, more efficient algorithms and an advanced computing network that is capable of processing the diversity and volume of data that networked sensor systems typically produce. To overcome this challenge will require collaboration between computer scientists, data analysts, and ecologists to design and implement cutting-edge data processing methods, which will yield meaningful insights about ecosystem health, and support decision makers to manage conservation.

Networked sensor systems need to develop further as integrated biodiversity monitoring approaches become increasingly necessary to understand and address biodiversity loss, and to ensure sustainable management of ecosystems and the provision of their services. However, the challenges outlined above highlight the need for future research and practical solutions in this field in order to improve their capability and versatility for researchers and practitioners. We would like to reiterate the increasing need to develop and pool our efforts across new interdisciplinary research workflows, including computer science, ecology, engineering, and data science, to make networked sensor systems for integrated biodiversity monitoring robust, cost-effective, and accurate.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

We provide the soundscape of the Marburg Open Forest covering nearly 3 years of audio recordings from 48 AudioMoth devices (Figure 18; 14,093,659 files, with 1-min recordings per file followed by a 1-min break, running 24 h per day from April 2020 to October 2022 during about 2 weeks every month, in 48 kHz 16-bit mono WAV format, totalling 77 TB). The data are available via https://doi.org/10.17192/fdr/187.2, where we offer a compressed sample from a single AudioMoth device for direct download (130,873 files, March to December 2021, MP3 format, totalling 30 GB). Other data generated in the Nature 4.0 project can be found through references in the respective sections or are available from the corresponding author upon reasonable request.

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